# Towards Individuated Reading Experiences: Different Fonts Increase Reading Speed for Different Individuals

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In our age of ubiquitous digital displays, adults often read in short, opportunistic interludes. In this context of *Interlude Reading*, we consider if manipulating font choice can improve adult readers' reading outcomes. Our studies normalize font size by human perception and use hundreds of crowdsourced participants to provide a foundation for understanding which fonts people prefer and which fonts make them more effective readers. Participants' reading speeds (measured in WPM) increased by 35% when comparing fastest and slowest fonts without affecting reading comprehension. High WPM variability across fonts suggests that one font does not fit all. We provide font recommendations related to higher reading speed and discuss the need for individuation, allowing digital devices to match their readers' needs in the moment. We provide recommendations from one of the most significant online reading efforts to date. To complement this, we release our materials and tools with this paper.

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## 1 INTRODUCTION

We spend more time on our screens now than ever before, trying to consume a rapidly growing amount of information through digital devices. Reading quickly and comprehending this ever-growing body of information is integral to work, leisure, social interaction, and personal advancement. The difficulty of coping with this information overload is well documented [43]. The ability to "keep up" with the proliferation of personal information streams, such as social media, and workplace information streams, such as email, is vital. Several studies spanning 10 years show adult readers across the United States and Europe continue to struggle with reading speed and comprehension [3, 4, 54, 62, 63, 102].

We posit that customizing reading experiences with font choice can lead to significant real-world improvements in digital tools and applications (e.g., e-readers, web-browsers, and reading applications on phones). Prior research has shown that tuning the font family, character spacing, and line spacing of text can significantly improve the reading performance of school children [97]. Early results from the same non-profit organization, Readability Matters, show that manipulating these text formats can increase accurate reading speed among adult readers by 20% or more [30]. Notably, current settings in e-readers provide options for readers to adjust the font family and size of the text. Motivated by these early but promising results, in this work we ask:

***What gains in reading speed and comprehension are possible by manipulating font choice alone?***

To answer this question, we conduct remote readability studies, by recruiting and studying hundreds of paid crowd-workers aged 18–71, reading in their everyday reading environments. We focus our attention upon *Interlude Reading* [108], which we define as an everyday reading context on digital devices where people read a few paragraphs worth of content. In Interlude Reading, short passages, or subsections of a longer document, are read interleaved with other tasks. Interlude Reading is a reading context that falls between Glanceable and Long-Form Reading [2, 16, 28, 38, 92, 104].

To systematically compare 16 common fonts, we designed a study to evaluate participants' preference for fonts and measure reading speed and comprehension. This design is supported by results from our two preliminary studies. Our first study "Accelerating Adult Readers with Typeface: A Study of Individual Preferences and Effectiveness" [107], shows initial evidence that font preference does not predict effectiveness. In this paper we re-analyze the results from our prior work to show that the size of a font (measured as x-height, average character height or width) affects preference. This new result shows a need to control for and normalize font size to better understand individual preferences and effectiveness. Our font normalization process uses Times at 16px as the reference font[1]. After selecting the reference font, we computed three new font sizes per font for the 15 remaining fonts. Each new font size corresponds to matching the reference (Times) in x-height, average character height, and average character width. We then conducted a perceptual task to derive a crowd-driven size normalization for each font. Next, using an improved study design featuring this set of normalized fonts, we conducted our large-scale study on Amazon's Mechanical Turk to evaluate the preference and effectiveness (speed and comprehension) of our newly normalized fonts.

The results from our remote readability studies focus on reading speed, while we attempt to account for font size, preference, and familiarity. While our methods sacrifice internal validity by remotely studying reading behaviors, we hope to provide applied validity by studying participants' reading behaviors in their everyday environments.

Our results show that no single factor predicts reading speed, and interestingly, preference does not predict speed even when font size is controlled. Our main takeaway is that different fonts work best for different people. While our results point to some broad recommendations regarding font choice for older readers, we believe future work is needed to answer

[1] 16px is the default font size in Firefox and Chrome.

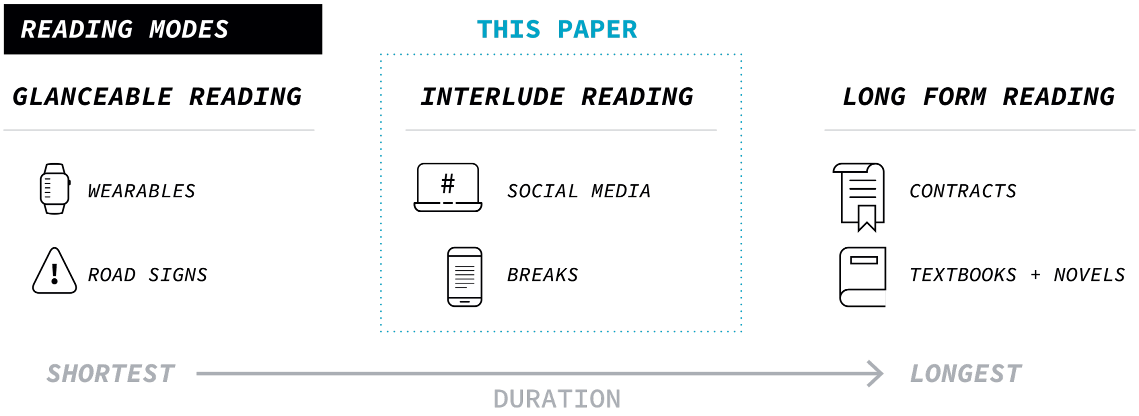


Fig. 1. Reading modes can be viewed on a duration continuum, ranging from the well studied domains of Glanceable Reading (few words, few seconds) to Long Form reading (long documents, minutes to hours). Interlude Reading, as introduced in this paper, falls between these two reading modes. We define Interlude Reading as the kind of reading that happens in a single brief sitting (i.e., a few paragraphs worth) or at short opportunistic interludes.

this question in a more controlled environment. By focusing our results on the individual, we see a potential 35% increase in reading speed (comparing fastest to slowest fonts) while maintaining comprehension. These potential gains are possible through changing font alone.

These results inform a discussion about the potential for personalizing font choices, which can guide future reading applications and, more generally, any other text-heavy digital resource. If the right reading tools are made readily available to all, the cumulative impacts can be significant and widespread. Potential impacts range from improvements to struggling readers' learning outcomes, more effective ingestion of reading material by college students, and quicker information intake in high-paced business settings. Our results show potential gains in reading performance can be obtained by reading in one's personally optimal font, tested with remote crowd-workers using online tests. Further, to help future researchers, we open-source our web applications and reading materials with this paper[2].

## 2 RELATED WORK

With the rise of remote studies, there is an opportunity to explore, describe, and leverage digital mediums' flexibility to improve reading experiences outside the traditional lab setting. Reading in short opportunistic interludes occupies a central role in textual consumption, as the information age increasingly drives individuals to consume more information. Our work thus focuses on a specific type of everyday reading we term *Interlude Reading*, a common everyday reading context for adults on digital devices, which falls in a continuum between reading at-a-glance and longform reading (Fig. §1). Researchers have started exploring this reading mode using remote and in-lab study methods [39, 92, 93, 107]. This section reviews how digital reading research has evolved over two decades, starting with Boyarski's foundational 1998 paper [21]. We cover relevant work about the effects of font features on reading performance. We end with a discussion of prior work in the space of font preference, aesthetics, and typography as they relate to reading effectiveness.

[2] Available at https://github.com/virtual-readability-lab/tochi-paper-materials-towards-individuated-reading

## 2.1 Types of Reading

*2.1.1 Long-Form Reading.* When reading for long periods, the primary task is reading, and all other tasks may be considered secondary and possible distractions. A common digital device used for long-form reading are e-readers [81]. In this reading mode, evidence for the impact of font choice on reading efficacy or experience is less available for primarily methodological reasons: studies linking typography to performance rely on participants reading short passages of text. Such efforts can nevertheless shed light on considerations for Interlude Reading. For example, Rudnicky and others showed that letter size and case were influential factors in reading performance [89], a finding reinforced by Bernard and Mills, and Chatrangsan and Petrie [13, 28].

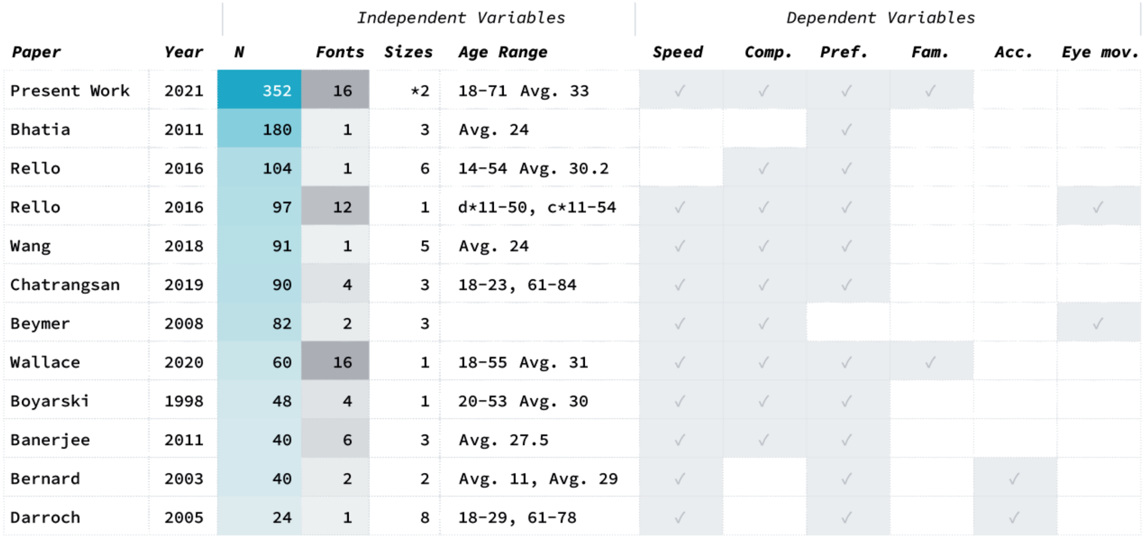
*2.1.2 Glanceable Reading.* In contrast to long-form reading, reading at a glance assumes that the reading activity is the distraction. In glancing at the text, the reader diverts attention from primary tasks: driving, walking, or social interaction. As such, in glanceable reading, the goal becomes one of imposing a minimal cost on the crucial non-reading activity by increasing reading effectiveness. In the domain of glanceable reading, performance differences between fonts are well documented [37, 38, 83]. The concept of legibility in at-a-glance reading revolves around the ability to collect understanding of content under time pressure. In both Western and symbolic Eastern languages, others have demonstrated that psycho-physical methods could differentiate the utility of individually optimal fonts [37]. Sawyer et al. specifically call out designers' propensity to focus on aesthetic concerns over performance concerns, especially in contexts where safety is paramount and the cost of failure high, such as in the automotive context [91].

*2.1.3 Interlude Reading.* We define Interlude Reading to capture opportunistic reading (during short breaks), quick information gathering, and content consumption through social media platforms. Examples are reading in a single brief sitting, on public transport, waiting in line, or taking a brief break to browse news, social media, blog posts, or to read sections of more extensive work. Information gathering of many types can fall under this umbrella. Increasingly, short, opportunistic interludes occupy a central role in textual consumption, primarily as information overload drives individuals to consume more information in smaller chunks and interleaved with other activities. Thus, Interlude Reading cannot be categorized as either glanceable or long-form, requiring separate research attention.

Interlude Reading aligns with easily digestible reading materials (i.e., a few paragraphs worth) and fits Carver's recommended range of 138–600 words per minute for reading with comprehension [26]. The reading length of a few paragraphs is also well-suited for shorter remote crowdsourcing tasks deployed on the web. This web-based naturalistic setting sacrifices the internal validity of prior in-lab studies [16, 21, 88], in exchange for greater ecological validity. While remote studies might suffer from reader distractions [98] and uncontrolled variables, such as viewing distance [56] and the physical size of digital text [120], it is easier to recruit more participants to offset this additional noise. To provide appropriate stimuli balancing naturalistic and practical considerations, we specifically source short passages of leveled reading material from a reading specialist (Sec. §5.1).

## 2.2 Past Efforts on Readability

There is a rich history of research exploring typography as a tool to enhance readability and reader efficacy. While past work has individually considered font preference, familiarity, comprehension, and reading speed [6, 7, 9, 14, 16, 17, 19, 21, 79, 88, 113], these factors can be tightly coupled. For the first time, our work considers these factors simultaneously, controlling for some and systematically varying others to address possible confounds.



| | | *Independent Variables* | | | | *Dependent Variables* | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Paper*** | ***Year*** | ***N*** | ***Fonts*** | ***Sizes*** | ***Age Range*** | ***Speed*** | ***Comp.*** | ***Pref.*** | ***Fam.*** | ***Acc.*** | ***Eye mov.*** |
| Present Work | 2021 | 352 | 16 | *2 | 18-71 Avg. 33 | ✓ | ✓ | ✓ | ✓ | | |
| Bhatia | 2011 | 180 | 1 | 3 | Avg. 24 | | | ✓ | | | |
| Rello | 2016 | 104 | 1 | 6 | 14-54 Avg. 30.2 | | ✓ | ✓ | | | |
| Rello | 2016 | 97 | 12 | 1 | d*11-50, c*11-54 | ✓ | ✓ | ✓ | | | ✓ |
| Wang | 2018 | 91 | 1 | 5 | Avg. 24 | ✓ | ✓ | ✓ | | | |
| Chatrangsan | 2019 | 90 | 4 | 3 | 18-23, 61-84 | ✓ | ✓ | ✓ | | | |
| Beymer | 2008 | 82 | 2 | 3 | | ✓ | ✓ | | | | ✓ |
| Wallace | 2020 | 60 | 16 | 1 | 18-55 Avg. 31 | ✓ | ✓ | ✓ | ✓ | | |
| Boyarski | 1998 | 48 | 4 | 1 | 20-53 Avg. 30 | ✓ | ✓ | ✓ | | | |
| Banerjee | 2011 | 40 | 6 | 3 | Avg. 27.5 | ✓ | ✓ | ✓ | | | |
| Bernard | 2003 | 40 | 2 | 2 | Avg. 11, Avg. 29 | ✓ | | ✓ | | ✓ | |
| Darroch | 2005 | 24 | 1 | 8 | 18-29, 61-78 | ✓ | | ✓ | | ✓ | |

Fig. 2. This table is sorted by the number of participants (i.e., column N). It summarizes the main independent and dependent variables from related reading studies. The dependent variables correspond to the following evaluation metrics, which appear consecutively in the table in abbreviated form: speed, comprehension, preference, familiarity, accuracy, and eye movements. All checked columns indicate the use of the variable in the listed study; however, note that implementations vary between studies. *Our present work is the first to control for size per font based on participant perception. Therefore we have a unique normalized size per font which we compare to the original font size (hence two sizes tested per font).

Conducting readability studies is difficult given the number of factors that need to be considered simultaneously. This is compounded by the evolving diversity of devices, screen sizes and resolutions, and available fonts. For example, research from the early 2000s often studied font sizes ranging from 10–14 points. Rendering fonts at 14 points on a mobile device today would produce a different visual font size compared to a monitor from the early 2000s. The fonts we commonly read in on the web have changed as well. For example, based on Google Font Analytics, Roboto and Open Sans account for 51% of total font views today; and Lato, Montserrat, and Oswald account for another 11%. This evolving set of constraints presents a need to explore new remote methods to study readability across a variety of devices and contexts using modern fonts.

Our work derives its design from prior in-lab studies [16, 19, 21] to develop novel approaches for collecting data remotely to help discern subtle effects, which in some cases affirm and, in others, refute prior results. In what follows we include a detailed comparison of our work with prior studies, summarized in Fig. §2.

*2.2.1 Comparing Individual Studies on Readability.* We recognize the efforts of many past researchers covering similar areas as our work. It is essential to acknowledge the similarities and differences chronologically so future work can build on these combined efforts as readability research continues to change in response to innovations.

Many early studies from the Human-Computer Interaction community laid the groundwork for the methodologies in subsequent studies. They provided initial evidence of the relationships between font size, preference, and effectiveness, while relying on smaller numbers of fonts and participants. Boyarski et al. [21] studied 4 fonts (Georgia, Verdana, Verdana Italic, and Times Roman) in a lab setting. They recruited 48 University participants to study reading speed, comprehension, and preference. They found anti-aliasing did not decrease the preference for a font, at least for the 10 point size they tested. Compared to recent studies, 10 point size is not commonly studied because monitors have changed in size and physical capabilities, thus making the visual size of 10 point size text appear smaller than it used to.

Bernard et al. ran four studies building on Boyarski's work by expanding the sizes and fonts studied [13–16]. Bernard et al. [13] studied the effects of font type and size on the reading time and comprehension by older adults aged 62 to 83 in a lab setting. They recruited 27 participants to compare Times New Roman, Arial, Georgia, and Verdana in two different sizes per font by reading aloud. Comparing font sizes 12 and 14 points, they found that participants preferred larger fonts. In a follow-up study, Bernard et al. [14] recruited 60 participants to read text out load to measure reading speed, preference, and errors. Participants read in eight fonts (Century Schoolbook (Schoolbook), Courier New (Courier), Georgia, Times New Roman, Arial, Comic Sans MS, Tahoma, Verdana) in three sizes (10, 12, and 14 points). They found fonts at 10 point size were read significantly slower than fonts at 12 point size. In a subsequent study, Bernard et al. [16] recruited 40 participants in a lab setting to compare reading speed and preference for Arial and Times at 12 and 14 point sizes. Their results show that font size affects preference. Our work builds on this previous research by using fonts normalized by human perception of size to help uncover additional relationships between preference and font attributes.

Prior work has studied an ever-increasing set of font sizes, primarily on desktop computer monitors. With the advent of smaller screens on mobile devices, Darroch et al. [31] investigated the effect of font sizes ranging from 2 to 16 points on hand-held computers in a lab setting where participants read silently. They recruited 24 participants (12 old and 12 young) to compare reading speed and self-reported preference. Their results indicated that neither age nor preference affected reading speed.

As eye trackers grew in popularity and became more widely available, several researchers seized this opportunity to enhance readability research validity. Beymer and Russel [18] developed WebGazeAnalyzer, to monitor reading performance using an eye tracker to record fixation duration. Building on this idea of studying readability in a lab setting using eye tracking, Beymer et al. [17] recruited 82 participants to compare readability and comprehension with Helvetica and Georgia in sizes 10, 12, and 14 points. They found that for smaller font sizes, fixation durations were significantly longer. While this resulted in slower reading, the results were not statistically significant. This work with eye trackers in lab settings conflicts with similar prior results stating that font affects reading speed [16]. While eye trackers add internal validity to in lab readability studies, accurately tracking eyes remotely is presently impractical. However, this may well change in the future by combining research that controls for head position and tracks eye movements, making eyetracking research possible without dedicated hardware [56, 68, 74].

Studies have remained split on the relationships between font size, preference, and reading speed. For example, Bhatia et al. [19] studied the effect of font sizes (10, 12, and 14), italics, and color on readability and likeability within a group of 180 undergraduate students in a lab setting. They found participants performed better on pages with no italics and high italics compared to moderate italics. Contrary to prior work, their survey results showed font size has no statistically significant effect on participants' rating of likeability. In contrast, Banerjee et al. [6] found participants read significantly faster and preferred the largest font size in their study, 14 point. They compared subjective preference and reading speed and comprehension in a lab setting with 40 young Indian adults. They read aloud in six different fonts (Times New Roman, Verdana, Georgia, Arial, Courier, and New Tahoma) in sizes 10, 12, and 14 points.

With time, the amount and type of text content consumed on digital devices has increased. Researchers began to investigate the effect of font familiarity. Beier and Larson [9] studied the relationships between font familiarity, reading speed, and preference. They recruited 60 participants from a University, aged 20-52 (avg. 28), in a lab setting. Our measures for font familiarity resemble their condition of studying a participant's familiarity with common letter shapes.

As the variety of devices grew and the size of screens grew larger, Rello et al. [88] argued that much previous work is outdated due to early studies using font sizes 14px and below and participants reading aloud. Their study, conducted in a lab using eye trackers, proved that font size matters and that the technology underpinning readability research has fundamentally altered how we study it. Their study proposes that future research should focus on a wider range of fonts using sizes above 14px. Our study covers 16 fonts with each of their sizes perceptually normalized to Times at a base size of 16px.

Building on Rello et al.'s work, recent research has studied larger font sizes in various languages in lab environments. Wang et al. [111] studied reading speed, comprehension, and subjective preference using Chinese texts in a lab setting. They recruited 91 participants with an average age of 24 years, to complete their studies on mobile devices. They considered four typographic variables: font size (11, 14, 17, 21, 26 points), line spacing, paragraph spacing, and page margin. Notably, they created models of touch interactions to predict reader satisfaction with typography designs. In their conclusion, they call for individuated or personalized reading experiences. Chatrangsan and Petrie [28] studied the relationship between font family and size on reading speed, comprehension, and preference while skim-reading on tablet computers in a lab setting. They recruited 90 younger and older participants in Thailand and the UK to read in Thai and English, respectively. They compared 3 font sizes (14, 16, and 18 point) in 4 fonts across both groups - UK: Times New Roman and Arial; Thailand: serif (TH sarabun) and sans-serif typeface (Kanit). Participants picked their most preferred font among 6 possible combinations. They found that reading speed and comprehension significantly improved at size 18 point in both countries. While our work studies fonts in the English language, we hope our methods can be replicated and extended in other languages.

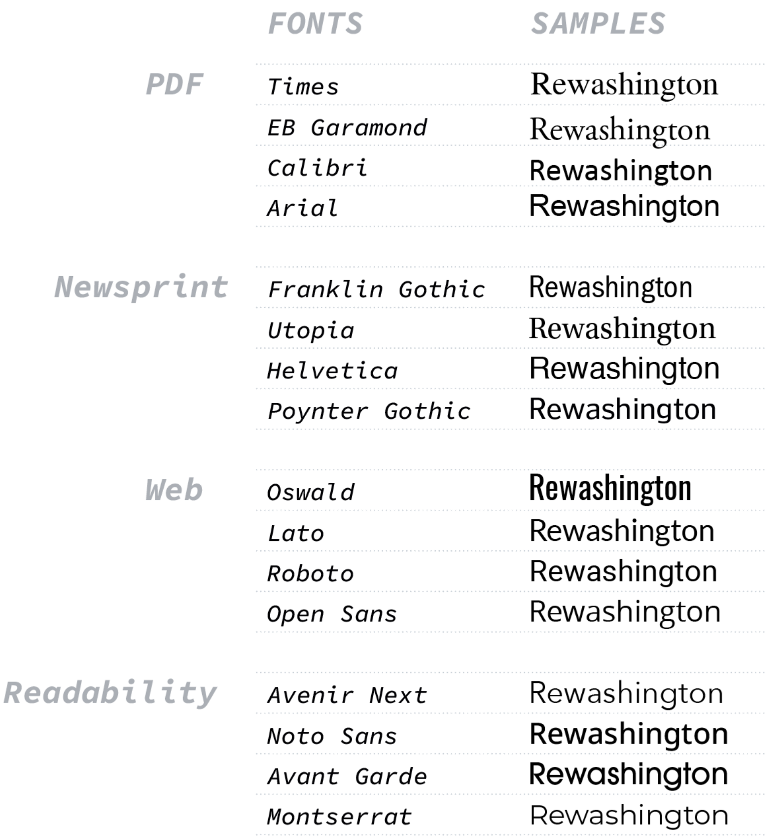
*2.2.2 Deriving Font Preference and Controlling Font Size to Study Effectiveness.* While some fonts are more appropriate for headers, body text, or even stylistic headlines, the effectiveness and preference of a font can be subjective [65]. How then can people select their most preferred font among a growing number of possibilities? O'Donovan et al. identified the difficulty modern graphic designers face selecting their preferred font from many fonts [72].

To derive someone's definitive ranking for preference, researchers in the HCI Community often use pairwise comparisons [46, 75, 80, 119]. Our approach to finding a participant's preferred fonts builds on the ideas from Boyarski et al. [21] and Wallace et al. [107] by using a toggle test on a single screen to definitively rank a participant's font preferences for body text. Our current work includes one fundamental difference from the past work discussed–our preference test controls for perceived font size. Past work has shown font size and preference are interdependent [14, 17]. Some fonts have been designed specifically to appear larger than others when rendered at the same size, to give them an advantage. For example, typographers have intentionally manipulated font attributes, such as x-height, in the case of Georgia, to give it a larger perceived size compared to traditional fonts [21]. Prior studies do not control for font size based on human perception and instead compare fonts in the same fixed pixel size per condition [16, 19, 88, 107]. By controlling font size based on human perception, our tests decouple font size from our results.

*2.2.3 Controlling for Font Aesthetics and Reading Environments.* Prior work has identified font as a straightforward tool to optimize reading performance [2, 103]. As aforementioned, font choice can help mediate reading ability in both at-a-glance and long-form reading [13, 28, 37, 93].

There are differences in font attributes across individual fonts that we consider but do not control for. For example, Burmistrov et al. show that light and ultra-light fonts also induce higher cognitive load [24]. While we do not control for this, our work studies fonts with thinner stroke widths such as Montserrat and Avant-Garde that readability experts recommend for reading body text [29]. To provide a generally safe line spacing to control for variations in the length of ascenders and descenders per font [20], we use a fixed-line spacing of 1.5. This decision follows the recommendations of Paterson and Tinker [76] and Rello et al. [87, 88] to ensure consistent readability and comprehension given a variety of fonts. Our results point to future work to study the individuated differences for other design choices such as character and word spacing.

In non-lab settings, participants read with the device they have in-hand, thus posing potential validity issues when studying readers in their natural reading environments. Duchnicky and Kolers [40] investigated the effect of display size on reading



| | FONTS | SAMPLES |
|---|---|---|
| PDF | Times | Rewashington |
| | EB Garamond | Rewashington |
| | Calibri | Rewashington |
| | Arial | Rewashington |
| Newsprint | Franklin Gothic | Rewashington |
| | Utopia | Rewashington |
| | Helvetica | Rewashington |
| | Poynter Gothic | Rewashington |
| Web | Oswald | Rewashington |
| | Lato | Rewashington |
| | Roboto | Rewashington |
| | Open Sans | Rewashington |
| Readability | Avenir Next | Rewashington |
| | Noto Sans | Rewashington |
| | Avant Garde | Rewashington |
| | Montserrat | Rewashington |

Fig. 3. The 16 fonts used in our studies chosen from 4 categories: PDF, Newsprint, Web, and Readability. The goal was to select a group of 16 fonts that cover common use cases and are frequently encountered by potential participants. The Samples column contains "Rewashington" rendered in each font, for additional visual comparison. Please see Appendix §A for the filenames used for each font.

scrolling text and reported little to be gained by increasing display size to more than four lines either in terms of reading speed or comprehension. Resiel and Shneiderman [85] confirm their findings, showing comprehension rates on smaller screens are generally equivalent to their larger counterparts. While participants in our study use different displays, the interface size is fixed to control any extenuating factors that might affect reading speed, comprehension, and preference. However, future work in remote readability should evaluate how to control the visual size of fonts and screen viewing distance [56, 120].

## 3 STUDY MATERIALS

This section discusses how we selected the fonts and designed the web interfaces to enable our remote reading studies.

### 3.1 Selection of Fonts

There are over 750,000 digital fonts and counting [99]. Our study aimed to capture popular fonts across various media and periods ranging from print to digital. The sixteen fonts (Fig. §3) used in our studies [107] were based on the following criteria:

*Four PDF Fonts:* We selected four of the most common fonts used for (digital) documents[3]. PDFs are a common medium that contain a vast amount of text that people read in digital environments. Times and Arial are not only common PDF fonts; they have been frequently studied in prior work [16, 88]. Readers are more likely familiar with fonts selected from this category, and familiarity is one factor posited to affect preference and reading speed [7].

*Four Newsprint Fonts:* We selected four of the most popular fonts from newspapers and print media [33, 59]. If fonts originally designed for newspapers and other print media do not compare favorably with fonts designed for digital screens, future researchers studying readability on digital devices can leave out these fonts (see Sec. §7.3). Even within this group, Helvetica is a common font used across devices and software. While it was originally designed in 1961, it has since been redesigned for screens.

*Four Web Fonts:* We selected four of the most common fonts used on websites[4]. Based on Google Fonts Analytics, Roboto and Open Sans have accounted for more than 50% of all views. While Oswald is commonly used for titles and headers, it has unique attributes among our selected fonts, including tight character spacing and particularly thick stroke width.

*Four Readability Fonts:* We selected four fonts recommended by readability experts [29, 96] not otherwise covered by the other categories. Field studies conducted by these readability experts show these fonts have led to reading speed gains in children. Also, these fonts possess attributes thought to increase readability, such as larger x-heights than most fonts. In particular, Noto Sans was specifically designed to be readable on small screens.

Of these fonts, we selected Times as a baseline to study perceived sizes in fonts and reading speed and comprehension. Times is one of the most common fonts both on screen and in printed text, and appears in many other reading studies [6, 16, 21, 28]. We also chose Noto Sans as a baseline to compare reading speed and comprehension because it was the best performing font in our previous study [107].

*3.1.1 Typographic Considerations.* Every font contains many attributes in its unique anatomy, and the present study does not attempt to tease apart effects of individual attributes. Instead, we selected 16 fonts with diverse font attributes that are commonly available across platforms. While there are notable omissions, including monospaced fonts, we believe this current list covers several unique categories and classifications.

Prior work has studied serif vs. sans-serif fonts in-depth [14, 17]. Our font selection has 3 serif and 13 sans-serif fonts across different classifications. We include various fonts classified as sans-serif: 3 Neo-Grotesque, 3 Geometric, 3 Humanist, 3 Gothic, and 1 Modern; our serif fonts include: 2 Old Style and 1 Transitional. Future work on serif vs. sans-serif fonts can focus on fonts from the same family, such as Source Sans Pro, Source Serif Pro, and Source Code Pro.

All of our study fonts have regular character width, while Oswald and Franklin Gothic are condensed. We also have specific pairs of fonts that share similar design histories and attributes. Arial and Helvetica have similar metrics and anatomy, such as x-height, ascenders, and descenders. Open Sans is a general use font derived from Noto Sans. Typographers designed Noto Sans for the small screens on Android devices. Poynter Gothic and Franklin Gothic share a similar origin but are different widths. Four of our fonts (Arial, Helvetica, Avenir Next, and Times) are likely to be very familiar to readers since they are pre-installed in macOS and Windows/Office. Also, 5 fonts have hinting (i.e., are engineered for reading on screens with low resolutions): Arial, Helvetica, Calibri, Noto Sans, and Times.

Half of the study's fonts have anatomical features that have been associated with improved readability, such as generous x-height, open apertures, low contrast, wider forms, and short ascenders: Calibri, Noto Sans, Open Sans, Lato, Utopia, Montserrat, Arial, and Helvetica. Our other study fonts that do not cover these readability features provide a variety of other

[3] Found by analyzing a corpus of 2302 PDF documents. While we used an internal Adobe corpus, the documents themselves were curated from freely available documents on the web, without topic constraints, so the conclusions should generalize to other general document collections.
[4] https://fonts.google.com/analytics [Accessed August 2019]

font anatomies and attributes previously discussed in this section. We provide our large crowdsourced dataset covering these different fonts to help other researchers expand on our results[5].

### 3.2 Web Interfaces to Study Readability

We conducted our studies remotely using custom made web interfaces and recruited paid crowdworkers from Amazon Mechanical Turk. In this remote study environment, participants read in their natural environments, using their own devices. While this increases the applied validity of our results, it may generate additional noise. While crowdworkers may provide different data than participants in a laboratory setting, we believe the large number of participants we can recruit remotely compensates for individual noise. The following sections discuss how our web interfaces and methods control various factors to increase internal validity.

*3.2.1 Measuring Font Preference.* To measure font preference, we developed a font toggle test that determines a participant's favorite font through a double-elimination tournament [107]. Participants toggle between pairs of fonts and then choose their preferred font of the pair, using the prompt: "What font is easier for you to read in?" (Fig. §4). This prompt was chosen because our focus is specifically on finding fonts participants prefer to read with, rather than fonts they prefer in general.

Our toggle test is a simple and efficient method for assessment, motivated by other common pairwise comparison tasks, such as eye exams and hearing aid adjustments [71]. To evaluate this approach, we ran a pilot study on UserTesting.com where participants used the think aloud method as they selected which font they preferred to read in. Notably, when participants saw two similar fonts, such as Open Sans and Noto Sans, they took longer to decide but ultimately selected the font they felt caused "less eye-strain."

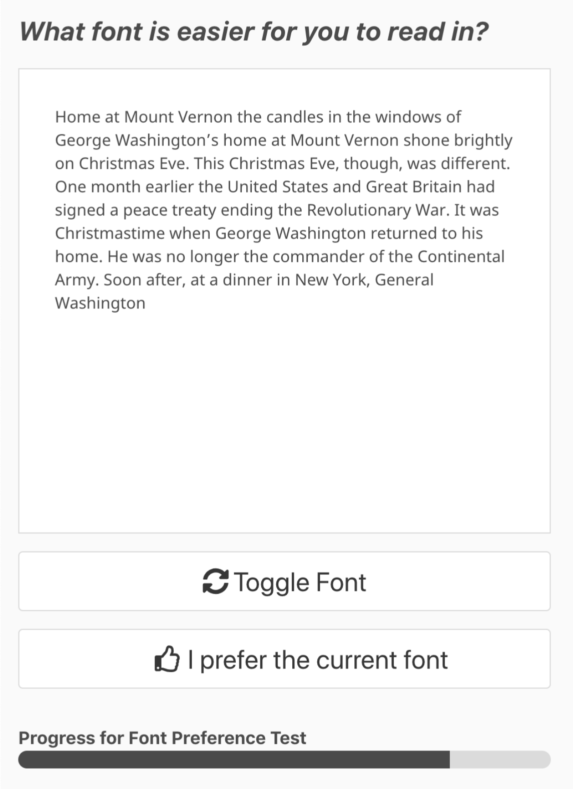
*3.2.2 Measuring Font Effectiveness.* To measure font effectiveness, we had participants read passages in different fonts while their reading speeds and answers to multiple-choice comprehension questions were recorded. The Interlude Reading setting was particularly suitable for our web-based studies. Having short, paragraph-length texts on different topics allowed participants to remain engaged and on-task. Participants were given the following instructions:

> "During the reading sections, please read as quickly as you can, without reading out-loud or re-reading. However, be prepared to answer comprehension questions about the reading."

Reading speed is measured by starting a timer when text is rendered on the screen. When the participant selects the button to proceed, the timer is stopped. The proceed button is disabled for the first 2 seconds after the new text is rendered on the screen to prevent accidental clicks. Several research efforts have previously demonstrated the successful collection of behavior data and response times in a web browser using JavaScript [34, 84]. Also, several studies have agreed that online response times collected in web browsers are reliable within the range of tens of milliseconds [35, 95].

*3.2.3 Interface Considerations.* To add more control to our studies, the interfaces did not allow participants to alter the font size, text box width, or the browser's zoom level. We constrained the font sizes and text box width to fixed pixel sizes. These fixed interface dimensions help control scrolling behavior [64]. Participants across all studies performed the activities in their everyday environments instead of a lab setting. All participants reported their environments being adequately lit rooms. Scaltritti et al. found lighting within a natural range of values exert a limited influence on reading and legibility [94]. Because our study was run remotely and manipulated text using CSS, we could not control for anti-aliasing. However, our

[5] Available at https://github.com/virtual-readability-lab/tochi-paper-materials-towards-individuated-reading



*What font is easier for you to read in?*

Home at Mount Vernon the candles in the windows of George Washington's home at Mount Vernon shone brightly on Christmas Eve. This Christmas Eve, though, was different. One month earlier the United States and Great Britain had signed a peace treaty ending the Revolutionary War. It was Christmastime when George Washington returned to his home. He was no longer the commander of the Continental Army. Soon after, at a dinner in New York, General Washington

Fig. 4. Font preference toggle test: A participant toggles between pairs of fonts to decide which one is easier to read in. The interface is a fixed width of 420px regardless of the device. All text is rendered with a line spacing of 1.5. Custom JavaScript is used to ensure participants cannot modify the size of the interface or text. This toggle test is done repeatedly within a double-elimination tournament over pairs of fonts to determine a participant's preferred font. A participant toggles the font family used to display the sample text, then they stop on the font of the pair they prefer and click to indicate their preference, before moving on to the next pair of fonts.

metrics evaluate how individual experiences differ across fonts, font size, and reading speed. These evaluation metrics fundamentally differ from other lab studies that focus on the results as a whole [16, 88]. Our work provides approaches for conducting remote readability at scale.

*3.2.4 Incentives for Paid Crowdworkers.* Since our study was run remotely with paid crowdworkers, we could not observe their reading behavior with the same scrutiny as in a lab setting. However, our study methods and recruitment of paid crowdworkers provide incentives that contribute to the validity of our results. Payment for a task can extrinsically motivate crowdworkers [50]. Crowdworkers are also extrinsically motivated by the prospect of future payments. For example, if a crowdworker produces low-quality work, this can result in a rejection. This scenario decreases their approval rate resulting in fewer paid opportunities in the future [58]. To ensure our participants had prior experience performing remote tasks, our studies recruited crowdworkers with approval ratings of greater than or equal to 99%, and they must have completed at least 100 tasks on Amazon's Mechanical Turk. Also, paid crowdworkers may be intrinsically motivated to participate in tasks they are interested in [66, 67]. Paid crowdworkers might also be motivated to perform the task honestly because they are provided personal insights about their reading speed and preference in different fonts at the end of the study: (i) Their most preferred font, and their reading speed, measured in words-per-minute; (ii) Their fastest font, and their reading speed in it; (iii) An interesting fact about their most preferred font. Providing personal insights to help participants improve and evaluate themselves has proven to be an important intrinsic motivator in other studies [32, 84]. Further, because of the combination of 1) splitting texts into short paragraphs across multiple screens, 2) disabling the proceed button for the first few seconds of every screen, and 3) providing multiple-choice comprehension questions and surveys after every passage, participants were incentivized to complete the readings rather than just click through them. Given that our reading tasks require only a few minutes of concentration at a time, Interlude Reading is particularly well suited to study with crowdsourced research.

## 4 PRELIMINARY INVESTIGATIONS OF FONT SIZE AND PREFERENCE

Motivated by prior work showing that font size can affect readability, this section contains a re-analysis of data from our prior study [107], investigating the effects of perceived font size on preference. To control for these confounding effects of font size, we present a crowdsourced approach for normalizing font size that we then apply to the fonts in our main study on reading effectiveness (Sec. §5).

### 4.1 Additional Related Work on Font Size

Rello et al. call for future work to address the need to control for the "real size" of letters in a given font [88]. Rudnicky et al. discussed how readers process text through a normalization process to account for font size discrepancies [89]. This inherent normalization process can contribute to differences in reading speed between fonts. There is an example of prior work normalizing the height of characters to study character legibility from Chinese typefaces [121]. Our work focuses on fonts commonly used for the English language. These insights and examples from prior work motivate the need to normalize font sizes.

Not all fonts are created equal in terms of anatomies and attributes that affect the perceived size. Prior work has discussed how x-height can increase legibility [79, 113]. In fact, Georgia was designed to have a larger x-height compared to similar fonts to give a perceived advantage over Times [21]. At the same time, Times is designed to fit more words on a single page. We provide starting points for normalizing font sizes below.

### 4.2 Methods to Normalize Font Size

Our font normalization method uses images of glyphs from a given font, instead of relying on the font's OS/2 tables[6]. Recent work similarly analyzes images of glyphs instead of OS/2 tables to extract font size features [78].

To begin the font normalization process, we use Times at 16px as our reference font. We chose 16px because it is the default font size in modern browsers, such as Firefox and Chrome. After selecting the reference font, we computed three new font sizes per font for the 15 remaining fonts. Each new font size corresponds to matching the reference (Times) in **x-height**, **height**, and **width** (Fig. §5). The paragraphs below describe each normalization method in detail.

The normalization method for **x-height** is the simplest of the three methods. We adjust the font size of the target font until its x-height matches that of the reference font. To compute the x-height value of a given font we rasterize the glyph for the lowercase letter x at a given font-size. The height of this raster bitmap is known as the x-height for that font. The x-height for reference (source) font at a particular font-size is $F_s$, termed $sourceXHeight$, and the target font's x-height, $targetXHeight$. Then, we compute a $\Delta$ as ($sourceXHeight\ /\ targetXHeight$). Finally, we compute the target font's new font size $NewF_s$ so it matches the reference font in x-height: $NewF_s = F_s \times \Delta$.

[6] https://docs.microsoft.com/en-us/typography/opentype/spec/os2

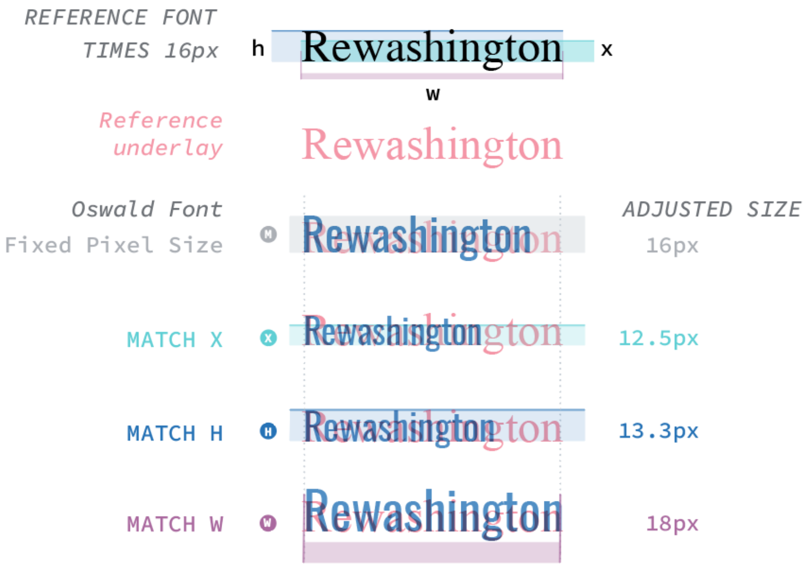


Fig. 5. Text can be normalized by matching its x-height (X), height (H), or width (W) to a reference font. In our study, Times at size 16px was used as the reference font when normalizing other font sizes. Here the text "Rewashington" is rendered in Oswald and normalized to match Times in size for each normalization method and at the default size of 16px (M = match size). Notably, Oswald has a much larger x-height and height than Times, resulting in a smaller adjusted size when matching according to these characteristics. Larger heights are common among many modern fonts designed for screens.

The computation for the average bounding box **width** of a font requires more steps. To begin, each character of a given font has a different width, known as the advanced-width of a glyph. Instead of relying on the width of a single character of a glyph, we compute a width of a string of Latin Characters (i.e., ABC...Zabc...z012...9). We compute each glyph's advanced-width from the string and add each advanced-width to get the string's resultant overall width (Appendix §B, Algorithm §1). Using this algorithm, we compute the resultant width for both the target and source fonts. Finally, to compute the target font's normalized font size to match the width of the source font at 16px we compute the Δ for width and then multiply it by 16px (Appendix §B, Algorithm §2).

The algorithm to compute the **height** of a given font is similar to computing the width. We do not rely on a single glyph's height, and instead, we use the same string of Latin Characters as above and compute each glyph's tight bounding box at a particular font size (e.g., 16px). Then we compute the minimum and maximum points of all bounding boxes. Such minimum and maximum bounding box points will provide a resultant height of the overall font. We compute the resultant height for both the target and source fonts (Appendix §B, Algorithm §3). Finally, to compute the target font's normalized font size to match the height of the source font at 16px we compute the Δ for height and then multiply it by 16px (Appendix §B, Algorithm §4).

### 4.3 New Findings on Font Size and Preference from our Prior Remote Readability Study

While prior work has compared fixed font sizes to each other [16, 88], we recognize that participants may perceive two fonts to be different sizes even when rendered at the same fixed size. We discovered this by re-analyzing our data from our prior published work "Accelerating Adult Readers with Typeface: A Study of Individual Preferences and Effectiveness" [107]. The following text features new results not previously published in our prior work [107], showing that font size influenced font preference during our pairwise comparison test. These new results motivate our new studies and study design changes in the current paper.

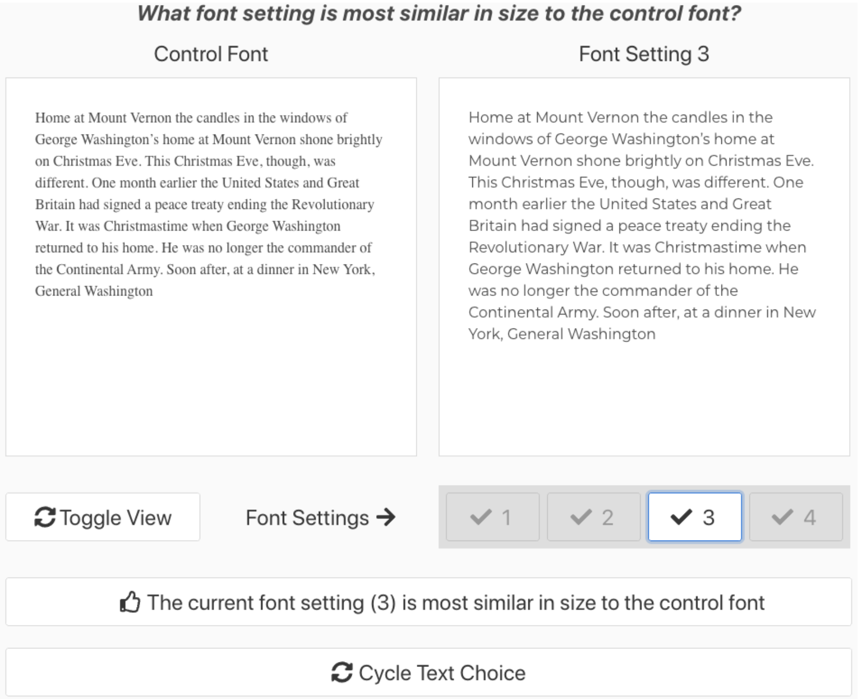
We conducted our prior Interlude Reading study remotely with 63 participants recruited from university mailing lists, UserTesting.com, and Amazon's Mechanical Turk. All fonts were rendered at size 16px similar to other research [112]. To measure whether perceptual font sizes affect reader font preferences, we first computed each font's **x-height**, average character **width**, and average character **height** using our methods described in Section §4.2. Using prior data collected from the font preference pairwise comparison test, we measured whether the winning font (i.e., the font the participant preferred) had the larger **x-height**, **width**, and **height**. We ran two-tailed t-tests of unequal variance. When considering which font had the larger **x-height**, the winning font was larger 52% of the time ($t(6012) = 3.7$, $p < 0.01$), for average character **width**, the winning font was larger 56% of the time ($t(6012) = 9.7$, $p < 0.01$), and for average character **height**, the winning font was larger 53% of the time ($t(6012) = 4.1$, $p < 0.01$). While font size proved significant, the relatively small difference in mean win rate per pairwise comparison indicates size was not the only factor driving font preference. We also consider qualitative feedback that participants had provided about what made them prefer specific fonts over others:

> P3: "I changed my mind multiple times while toggling. I think I prefer serif fonts for reading but prefer the look of sans-serif fonts."
> P6: "I liked bolder and bigger fonts. The fonts had to be linear and not curvy"
> P11: "I looked at the size of the fonts"
> P13: "It was larger, easier to read, and interestingly modern"
> P14: "larger fonts and good kerning and bold"
> P18: "I like different fonts based on what I am reading/writing, therefore I would choose the font based on the text and the size"
> P22: "I like the slightly bolder and slightly larger letters. these two things combined make the letters jump out of the screen better."
> P23: "I think that spacing between the characters, words, and lines of text and the weight of the texts (bold vs. not) was a huge indicator for me in terms of legibility and familiarity. Things I was familiar with seemed easier to read at times if they were a previously preferred font for reading. Size did not necessarily matter as much as spacing."
> P26: "Clear and large. I wear glasses and have neck strain so like large fonts."
> P42: "I thought my preferences were going back and forth depending on if I wanted bigger or darker text in the moment"
> P43: "Its easy to read, has a good boldness to it, and isn't too cluttered."
> P45: "font height seemed to make more readable, to a point, as did thickness"
> P51: "During the font (toggle) test, I found that I preferred fonts which were wider and more spaced out over fonts which were narrower and spaced close together. Therefore, if I found myself able to read faster over a sample text (without having to re-read it), I knew that this would be my preferred text amongst each set of pairings."
> P54: "It's a larger font that isn't too dark."

While this qualitative feedback provides general evidence that font preference is influenced by size, it also hints at the possibility of character spacing, stroke width, and several other font attributes. In our preliminary study [107], the two fonts that achieved the highest reading speed were EB Garamond and Oswald. EB Garamond has the smallest x-height and Oswald has the second smallest width across all fonts in our study. This might be explained by the fact that smaller fonts lead to a reduced reading span, which limit the magnitude of eye movements required between words and across lines [82]. These findings suggest a need to normalize font size to help systematically compare the preference and effectiveness of different fonts by reducing the possible confounds of perceived font size.

### 4.4 Perceptual Font Size Normalization Study

We designed a perceptual study to correct for how the average participant perceives size differences of fonts. While prior work proposes to normalize font sizes according to a particular attribute (e.g., x-height [14, 21]), we take a crowdsourced approach to finding the attribute, per font, that perceptually normalizes its size the best among four possibilities: matched (original size 16px), x-height, height, or width, using Times at 16px as a reference.



*What font setting is most similar in size to the control font?*

Control Font

Home at Mount Vernon the candles in the windows of George Washington's home at Mount Vernon shone brightly on Christmas Eve. This Christmas Eve, though, was different. One month earlier the United States and Great Britain had signed a peace treaty ending the Revolutionary War. It was Christmastime when George Washington returned to his home. He was no longer the commander of the Continental Army. Soon after, at a dinner in New York, General Washington

Font Setting 3

Home at Mount Vernon the candles in the windows of George Washington's home at Mount Vernon shone brightly on Christmas Eve. This Christmas Eve, though, was different. One month earlier the United States and Great Britain had signed a peace treaty ending the Revolutionary War. It was Christmastime when George Washington returned to his home. He was no longer the commander of the Continental Army. Soon after, at a dinner in New York, General Washington

Toggle View
Font Settings →
✓ 1
✓ 2
✓ 3
✓ 4
The current font setting (3) is most similar in size to the control font
Cycle Text Choice

Fig. 6. To normalize font size, crowdworkers see a control (reference) font in one panel and a target font in the other. They can toggle between 4 different target font settings, which corresponds to adjusting the font size to match the reference in x-height, width, height, and original size (16px). The settings are shuffled per participant. In this figure, Times is on the left, and Montserrat is on the right. Differences in effective font size become especially apparent when the same piece of text is rendered in two different fonts side by side.

#### *4.4.1 Study Design.*

Participants completed a perception study to select the best normalization method for each of our 16 study fonts and 4 tutorial fonts – used for practice sessions to familiarize participants with our study (Georgia, Verdana, Raleway, and Comic Sans). Our interface presented participants with two screens side-by-side, with the same piece of text rendered in two different fonts (Fig. §6). One of the screens always contained the reference font (Times), and the other screen contained a target font. Participants could click to toggle between four possible settings of the target font, one of which was the original font setting, and the rest corresponded to normalizing the font by x-height, height, or width. The four settings were shuffled per font, per participant. After toggling through all the settings, a participant would click to select the setting most similar in size to the reference. Participants could also swap the reference and target fonts, which facilitated quickly toggling back and forth between the fonts. There was also an option to change the underlying text passage.

We recruited 61 participants: 23 via university mailing lists, 18 professionals ranging from designers to engineers, and 20 crowdworkers from Amazon's Mechanical Turk. We did not collect demographic information for this study. Participants took, on average, less than 5 minutes to complete this study. The participants from university mailing lists and the professionals were provided a $5 Amazon Gift Card for completing the study. The university mailing lists consist of undergraduate

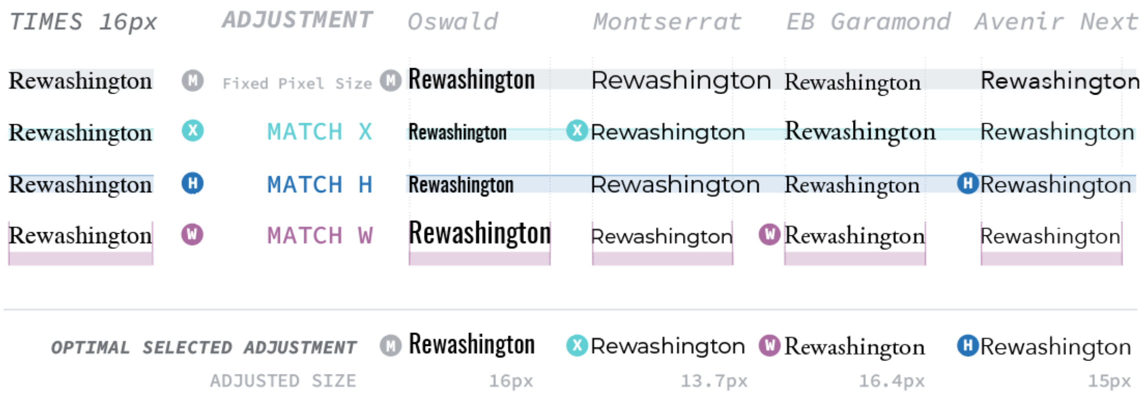
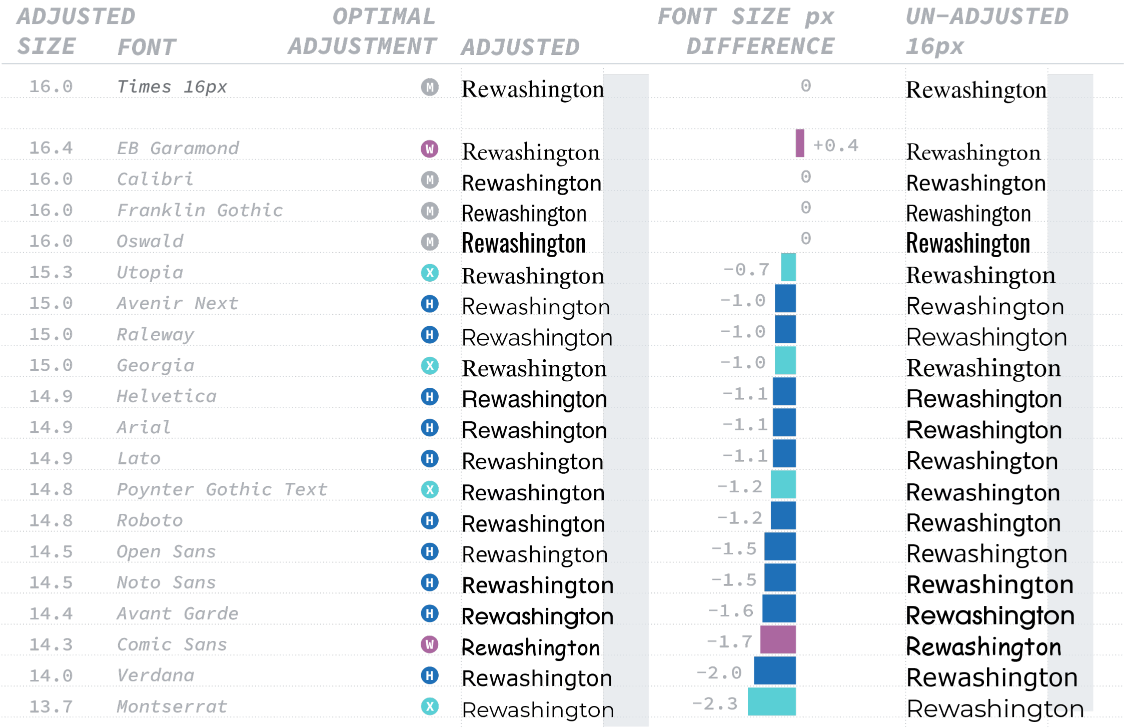


Fig. 7. When rendered at the same font size ('match size'), different fonts can have different perceived sizes. Depending on the criteria used to normalize font size (matching the x-height, width, or height of a reference font), the adjusted font size can vary drastically. Matching the height to the reference font was the most common normalization method chosen by crowdworkers. However, the assumption that a single criterion can normalize all fonts proves sub-optimal. We choose the optimal normalization strategy on a font-by-font basis, as determined by a population of crowdworkers. For instance, Oswald was left at its original 16px size, Montserrat was matched to Times by x-height, EB Garamond by width, and Avenir Next by height. Using these features to normalize the font sizes resulted in the final adjusted sizes indicated at the bottom of the figure, which perceptually are closer in size to Times at 16px.

and graduate students and faculty interested in Human-Computer Interaction, Computer Vision, and design. We recruited the professionals from an industry typography interest group, where it is common for researchers and practitioners to recruit participants for studies. The crowdworkers from Amazon's Mechanical Turk were paid $0.50 for their participation, matching the compensation used in similar tasks.

*4.4.2 Results.* The base font sizes for different fonts vary significantly (Fig. §7). For instance, EB Garamond is a smaller font, while Montserrat is naturally quite large. Comparing blocks of text rather than individual words demonstrates how the size difference gets amplified (Fig. §6). Previous papers that have mentioned the need to account for a font's perceived size have indicated that x-height should be the criteria used [14, 21]. However, our study results go against this common wisdom and show that the preferred way to normalize a font actually depends on the font itself. Fig. §8 shows the normalization factor that a majority of participants picked per font. In most cases, height was the most frequently-picked criterion. However, it is not always the best. In some cases, the differences between the best normalization factor for a font and another normalization factor can be quite large (Fig. §7). Rather than choose a single normalization strategy for all the fonts, we selected the most frequently chosen normalization strategy on a font-by-font basis, as determined by the crowd. This resulted in the final normalized font sizes plotted in Fig. §8. Despite some of the fonts being reduced in size from 16px, their final sizes are still above the recommended minimum font size for reading on a digital device [64].

*Takeaways:* There is not a single effective way to normalize a font's size. Normalization strategies depend on the font. Also, contrary to prior work, x-height is not always the best measure to use for size normalization [21, 79, 113]. Our normalization strategy is font-dependent and perceptually-motivated. We suggest that future work use this method to explore the impact of font upon reading performance. We used the individually normalized fonts for our main study on reading effectiveness, described next.



| ADJUSTED SIZE | FONT | OPTIMAL ADJUSTMENT | ADJUSTED | FONT SIZE px DIFFERENCE | UN-ADJUSTED 16px |
|---|---|---|---|---|---|
| 16.0 | Times 16px | M | Rewashington | 0 | Rewashington |
| 16.4 | EB Garamond | W | Rewashington | +0.4 | Rewashington |
| 16.0 | Calibri | M | Rewashington | 0 | Rewashington |
| 16.0 | Franklin Gothic | M | Rewashington | 0 | Rewashington |
| 16.0 | Oswald | M | Rewashington | 0 | Rewashington |
| 15.3 | Utopia | X | Rewashington | -0.7 | Rewashington |
| 15.0 | Avenir Next | H | Rewashington | -1.0 | Rewashington |
| 15.0 | Raleway | H | Rewashington | -1.0 | Rewashington |
| 15.0 | Georgia | X | Rewashington | -1.0 | Rewashington |
| 14.9 | Helvetica | H | Rewashington | -1.1 | Rewashington |
| 14.9 | Arial | H | Rewashington | -1.1 | Rewashington |
| 14.9 | Lato | H | Rewashington | -1.1 | Rewashington |
| 14.8 | Poynter Gothic Text | X | Rewashington | -1.2 | Rewashington |
| 14.8 | Roboto | H | Rewashington | -1.2 | Rewashington |
| 14.5 | Open Sans | H | Rewashington | -1.5 | Rewashington |
| 14.5 | Noto Sans | H | Rewashington | -1.5 | Rewashington |
| 14.4 | Avant Garde | H | Rewashington | -1.6 | Rewashington |
| 14.3 | Comic Sans | W | Rewashington | -1.7 | Rewashington |
| 14.0 | Verdana | H | Rewashington | -2.0 | Rewashington |
| 13.7 | Montserrat | X | Rewashington | -2.3 | Rewashington |

Fig. 8. Crowdworkers voted on which of three font size normalization methods (X = x-height, W = width, H = height) or original matched size (M) best matched the perceived size of Times at 16px. The chosen normalization method per font, according to majority vote, is listed under the column 'optimal adjustment'. The resultant change in px size per font from the chosen normalization method is listed under the column 'font size px difference', with the final 'adjusted size' in the leftmost column. The 'adjusted' and 'un-adjusted' (original 16px) sizes can be visually compared for each font, which was used to render the same string 'Rewashington' to make the size differences more salient.

### 4.5 New Remote Readability Study Design Considerations

Our prior study [107] validated the interfaces, methods, and manipulation checks that we adopt in the main study in this paper. In summary, our new findings result in three major changes from our previous remote readability study design [107]: 1) All font sizes are normalized based on the results of our perceptual font size normalization study (Section§4.4). 2) The preference test is a single double-elimination tournament instead of five smaller ones, to reduce the overall study duration. 3) Participants read in their most preferred font, Times, Noto Sans, and two random fonts. This provides the opportunity for every participant to read in their most preferred font, our prior work's most preferred and effective font Noto Sans, and the control font, Times.

## 5 METHODS: MAIN STUDY ON READING EFFECTIVENESS

The motivation of the present study was to determine what gains in reading effectiveness are possible by manipulating font choice alone, after controlling for perceived font size. To answer this question, we ran experiments on hundreds of participants on Amazon's Mechanical Turk, assembling one of the largest datasets of reader behavior relative to font.

### 5.1 Procedure

*5.1.1 Reading content.* In our prior work [107], we found differences in comprehension scores when participants read in different fonts. To reduce the confounding effects of topic and question difficulty, we worked with a reading specialist to carefully control the level and type of content used for this study. Our reading specialist collected a set of 15 text passages from Project Gutenberg[7], a repository of creative commons e-books. The passages were chosen to span different topics (history of science, biography, botany, etc.), with 12 non-fiction and 3 fiction passages. We believe these easily digestible topics are indicative of what people might read during Interlude Reading. Passages were curated down to 300–500 words, with minor adjustments to sentence structure and vocabulary to be at approximately an 8th-grade level (Lexile range[8]: 800–1200, Flesch score[9]: $60.5 - 79.8$). The reading specialist also prepared 4–6 similar-level comprehension and inference questions per passage. As such reading material has not previously been made available in the public domain, we are releasing it along with our paper for future reading studies[10]. We selected 9 non-fiction, and 3 fiction passages for the present study and further cut them down to 160–178 words. Then we split each passage approximately in half to be presented across 2 consecutive reading screens, without breaking apart sentences (69–93 words each). This allowed us to capture two measurements of reading speed per passage, to increase data robustness and allow us to filter outliers (Sec. §5.1.3). We selected 2 multiple-choice comprehension questions per passage, one corresponding to each half of the passage. In this way, participants would need to read both halves of the passage carefully to answer both comprehension questions correctly. We did not use inference questions for this study to keep the task difficulty more predictable.

*5.1.2 Study design.* Participants could complete the study on a device of their choice: desktop computer, laptop computer, tablet, or mobile device. Across participants, 35.5% used a desktop, 60.2% used a laptop computer, 2.3% used a tablet, and 2.0% used a mobile device. Our web server detects a participant's device using the commonly used library express-device[11]. Participants began the study with a pre-survey asking a range of questions, including about demographics (age, education, native language), reading experience (frequency, type of content, device of choice), vision (normal/corrected), disabilities (learning or reading), state (under the influence of drugs, medications, alcohol), and environment (lighting, time of day). All Pre-Survey questions are provided in Appendix §D and all Post-Survey questions are provided in Appendix §E.

After an instructional screen, participants proceeded to the practice phase, with short versions of both the preference test and effectiveness test, to get acquainted with the study flow (Fig. §9). The first phase of the main study was a preference test, run as a double-elimination tournament with 16 study fonts. The preference test was split into a competition block of 30 comparisons, followed by a validation block of 6 comparisons, randomly selected repeat comparisons from the competition block to measure a participant's self-consistency. The average preference consistency per participant was 72%. Participants used the toggle interface (Fig. §4) for the pairwise comparisons.

After the preference test, participants completed 10 rounds of the effectiveness test. Each round consisted of reading a passage split across two consecutive reading screens (69–93 words per screen), followed by two multiple-choice comprehension questions, and a mini questionnaire asking participants about their reading technique, as well as familiarity and interest in the topic matter presented, using a 5-point Likert scale. Each participant read a total of two passages in each of 5 fonts. Assignment of fonts to passages was randomized per participant. The 5 fonts used were as follows: Noto Sans (best overall font in term of preference and effectiveness from [107]), Times (commonly used as a baseline font [6, 16, 21, 28, 107]),

[7] https://www.gutenberg.org
[8] https://hub.lexile.com/analyzer
[9] http://www.readabilityformulas.com/free-readability-formula-tests.php
[10] Available at https://github.com/virtual-readability-lab/tochi-paper-materials-towards-individuated-reading
[11] https://www.npmjs.com/package/express-device

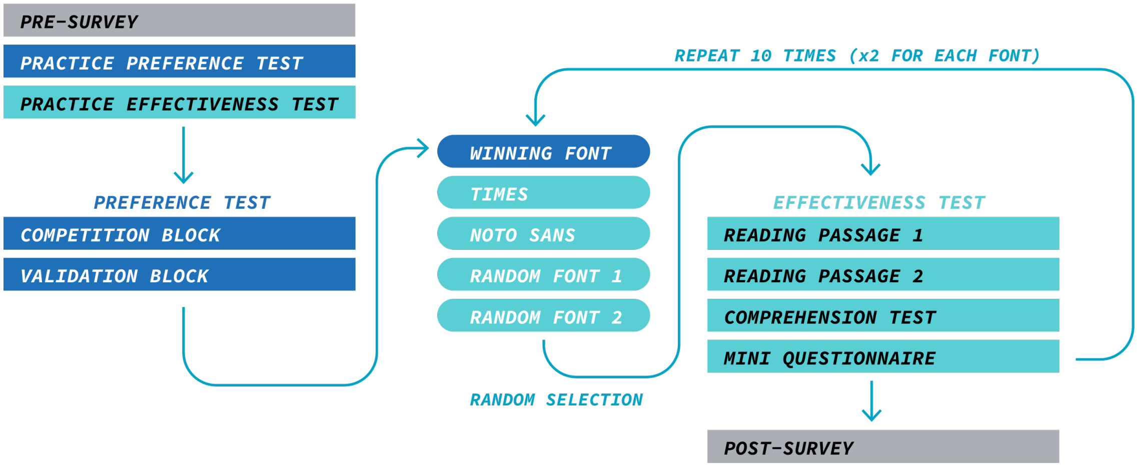


Fig. 9. Apart from a pre-survey to gather demographic information and reading experience, and a practice session, this study design consists of two distinct phases. In the first phase, participants complete a preference test: a double-elimination tournament with 16 fonts, leading to 30 pairwise comparisons (competition block) and 6 repeated pairwise comparisons (validation block). In the second phase, participants complete an effectiveness test: 10 rounds of reading 2 passages (average 70 words each), answering 2 multiple-choice comprehension questions (comprehension test), and answering 2 additional questions about passage interest and passage familiarity (mini questionnaire). The effectiveness test is run with 5 fonts: the winning font from the preference test, Times and Noto Sans as common baselines, and another 2 randomly selected fonts per participant. The study ends with a post-survey to evaluate the task's difficulty and collect familiarity ratings for the different fonts tested.

the participant's preferred font (from the preference test), and two randomly-selected fonts out of the remaining 13 study fonts[12]. As a result, across the 10 rounds of Interlude Reading, each font was used for two different reading passages (different topic, similar length). We recorded the time spent per reading screen and the responses to the study questions. The study ended by showing participants: (i) the font that won the double elimination preference tournament, i.e., their most preferred font, and their words-per-minute in it; (ii) Their fastest font, and their words-per-minute in it; (iii) An interesting fact about their most preferred font. A post-survey asked participants about their familiarity with each of the 20 study fonts (including the 4 practice fonts), their experience with the toggle interface, their reaction to their preferred font, and how effective they think their preferred font would be to read in.

*5.1.3 Data pre-processing.* We recruited 500 participants on Amazon's Mechanical Turk. We removed participants from the study's data if they met one of the following exclusion criteria: (i) did not submit pre and post surveys, (ii) did not self-report being "very comfortable" reading in English, (iii) self-reported being diagnosed with any reading or learning disability, medical or neurological condition, (iv) self-reported being under the influence of any drugs, medications, or alcohol, (v) had either of their WPM or reading comprehension scores outside the normal distribution as computed using the interquartile range method (IQR)[13], or (vi) had their preference consistency outside the normal distribution as computed using the IQR method.

To establish a range of reading speed indicative of Interlude Reading, we expand on Carver's recommended range of 138–600 WPM to account for standard error and remove any individual WPM measurements outside the range of 100–650

[12] In cases where the participant's preferred font was one of Noto Sans or Times, we would sample three, instead of two, randomly-selected fonts out of the remaining 14 study fonts.
[13] We removed reading speed measurements outside of the 100–650 WPM threshold before applying IQR for data removal.

WPM [25, 26]. Participants with an average reading comprehension score below 0.67 were also excluded (threshold determined by IQR method). To maximize the available data, WPM exclusions were applied to individual screens as appropriate. This resulted in an incomplete blocked design, the sparseness of which is handled with appropriate statistical methods (Sec. §6). After this filtering (removing 30% of participants), the data of 352 participants were used for reporting the results of this study.

*5.1.4 Participants.* Participants took on average 35 minutes to complete this study and were compensated $5 for their time. Of the 352 participants (46.1% female) that remained after data pre-processing, ages ranged from 18 to 71 years (average = 33): 8 were younger than 20, 139 were in their 20s, 132 in their 30s, 47 in their 40s, and 26 were older than 50. Data pre-processing did not skew the data's demographics. For example, after applying data pre-processing, participant's age distributions and education backgrounds remained relatively similar, see Table§1 in Appendix§F. Data pre-processing did not change the average age or minimum and maximum ages of our participants. After applying data pre-processing, the gender breakdown changed from (45.7% female, 54.3% male) to (46.1% female, 53.9% male).

While all participants reported being "very comfortable" reading English, 22% of participants were bilingual. In total, bilingual participants self-reported being able to read in 28 different languages. Participants reported reading using different devices for *leisure or personal interest*: 40.8% reporting reading on Desktop, 60.9% on Laptop, 35.4% Tablet, 23.8% Kindle or other e-readers, and 73.9% Paper. The following percentages of participants read using these devices for *work or study*: 53.8% Desktop, 70.8% Laptop, 18.1% Tablet, 7.1% Kindle or other e-readers, and 56.1% Paper. Participants reported reading articles written in English for *leisure or personal interest*: 56.1% Everyday, 7.1% Once a week, 31.7% 2–3 times a week, 2.8% Once a month, and 2.0% Less than once a month. Participants reported reading articles written in English for *work or study*: 36.3% Everyday, 11.3% Once a week, 35.1% 2–3 times a week, 7.1% Once a month, and 9.9% Less than once a month. Overall, our 352 participants read at different frequencies using a variety of devices for both work and leisure.

While we aimed to recruit a diverse pool of participants from the general population, the age ranges of our demographics better represent the digital reading population. Our most common age groups are readers in their 20s and 30s. When excluding readers under 18, the two most common age groups for digital reading are the 18-24 age group, followed by the 30-39 group [36]. Prior research from Pew Research has found that people aged 30 to 39 have the highest e-book usage [36]. Compared to older readers over the age of 65, readers under age 30 are reading more digital content due to its availability [27]

### 5.2 Evaluation metrics

To compare fonts in terms of their preference and effectiveness, we computed the following metrics for each font from the collected participant data.

- *Win Rate:* The percent of pairwise match-ups each font won during the font preference test.
- *Elo Rating:* Since the font preference test consisted of a double-elimination tournament, participants did not make every possible pairwise comparison. To account for the strength of each font in a pairwise comparison, an Elo Rating [42] was computed per font, per participant, with a starting value of 1500. Elo Ratings were averaged across participants to create an average Elo Rating per font. See Appendix §C for details.
- *Elo Disagreement*: This is the standard deviation across all participants' Elo Ratings per font. The greater the number, the less consensus there was among overall preference per font.
- *Preference Consistency:* The rate at which a participant's current font preference given a unique pairwise comparison matches their previous preference for the same pairwise comparison.

- *WPM:* We measured reading speed in words-per-minute (WPM) computed as $\frac{w \times 60}{s}$ where $w$ is the number of words in a passage and $s$ is the number of seconds spent reading the passage.
- *Speed Rank:* Per participant, we compared their WPM on the 5 fonts they read in. We treated this as an implicit pairwise comparison by sampling each pair of fonts out of the 5 fonts used and tracked which font of the pair had the higher average WPM. Across all participants, this produced a win percentage of each font against every other font, which can be interpreted as a speed rank for that font over all other fonts.
- *Comprehension score:* We measured comprehension as the percent of questions answered correctly. Each participant read 2 sets of passages per font and answered 2 multiple-choice comprehension questions per passage (selecting out of 3 possible answers per question). When we report comprehension score as a percentage, it is based on a total of 4 questions per font, per participant.

## 6 RESULTS: MAIN STUDY ON READING EFFECTIVENESS

In what follows, we report our analyses of the Interlude Reading behaviors of 352 crowdsourced participants, whose preference, reading speed, and comprehension were measured across different fonts. Results for each font, averaged over all participants, and measured by the metrics defined in the previous section, are presented in Fig. §10. Next, we consider population-level results by running a linear mixed effect model to look at how various independent factors (participant age, font, topic, etc.) affect reading speed and comprehension. Recognizing that averaging across all the participants can obfuscate finer trends in the data, we dig into individual differences to measure the effects of font choice at the individual participant level.

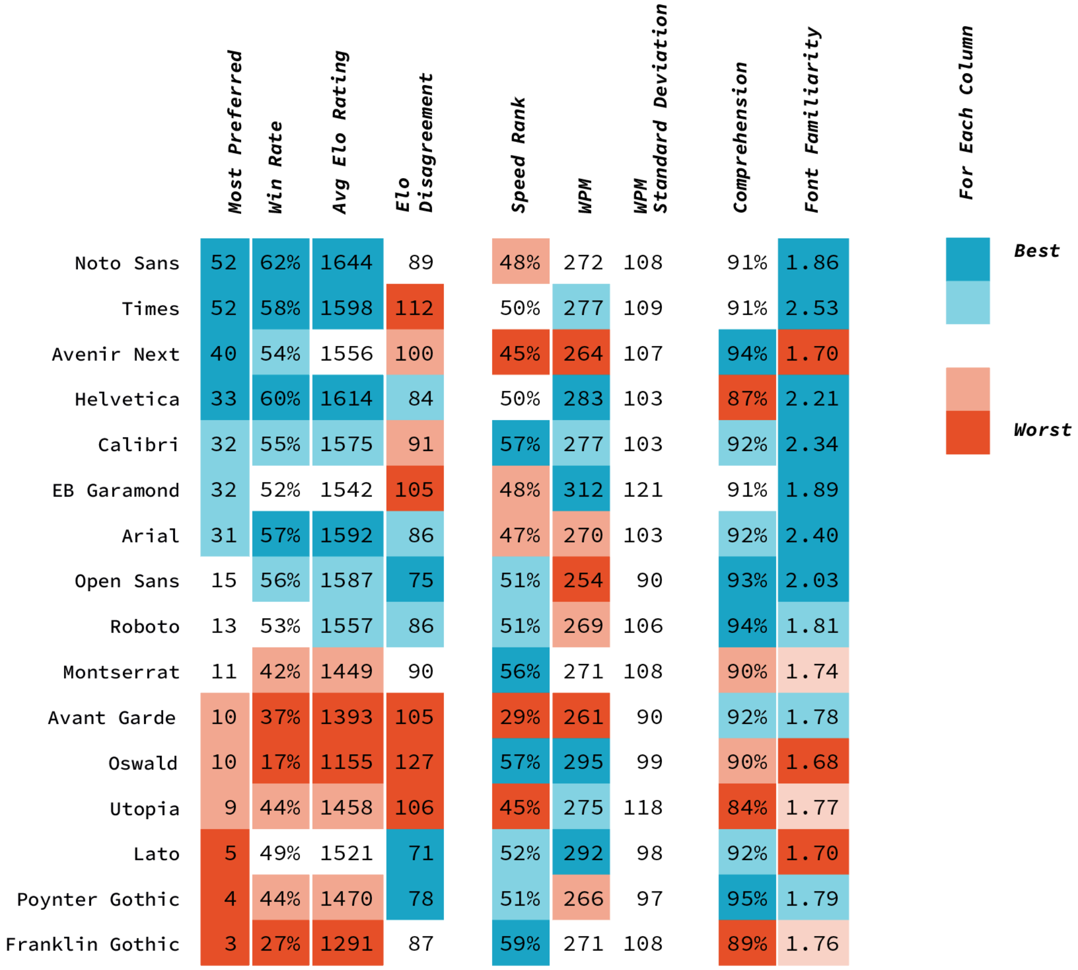
### 6.1 Population-level Results

*6.1.1 Model design.* To discover which factors influence reading speed and comprehension across our whole population of participants, we ran a linear mixed effect model (LME). Since any participant could potentially be shown any font, and all participants would be shown all passages, this model specifies participant ID and passage read as crossed *random effects* with intercepts per level of participant and passage, and constant slopes for both. The model specifies the following as *fixed effects*: participant age, reading device, passage order, screen order, font, non-fiction status, topic familiarity, topic interest, and font familiarity. Screen order refers to participants reading each passage split across two consecutive screens.

Using all participant data (N=352), we ran two models: one to assess the impact of the predictors on reading speed, and another for comprehension. We also re-ran both models on the subset of participants aged 35 and older (N=118), owing to known differences in how older readers process textual information [8, 10, 37, 39, 93, 116].

Effect sizes are reported as the $R^2_\beta$ statistic for all significant effects, following Edwards *et al.* [41]. Briefly, traditional $R^2$ is derived by comparing the total residuals of a fitted OLS regression model against the residuals of a null model, usually containing only an intercept term. Similarly, $R^2_\beta$ compares a fitted LME model against a null model in which all fixed effects are removed except an intercept, and the random effects are retained (preserving the covariance structure and any crossed/hierarchical relationships encoded in it). If the $R^2_\beta$ formulation were applied to a univariate OLS regression, it would in fact be equivalent to classical $R^2$. Since a large share of the variance in the outcome measure is dependent on the model's random effects (here, the between-participant differences represented by the participant factor, or the content/interest differences intrinsic to the passage factor), $R^2_\beta$ estimates for fixed effects will usually be relatively small. Therefore, for clarity, we also report unstandardized effect size measures (i.e., group differences and other raw measures).

Please refer to Appendix §G for additional details; and to Appendix §H for additional results not covered in this section.



| | Most Preferred | Win Rate | Avg Elo Rating | Elo Disagreement | Speed Rank | WPM | WPM Standard Deviation | Comprehension | Font Familiarity |
|---|---|---|---|---|---|---|---|---|---|
| Noto Sans | 52 | 62% | 1644 | 89 | 48% | 272 | 108 | 91% | 1.86 |
| Times | 52 | 58% | 1598 | 112 | 50% | 277 | 109 | 91% | 2.53 |
| Avenir Next | 40 | 54% | 1556 | 100 | 45% | 264 | 107 | 94% | 1.70 |
| Helvetica | 33 | 60% | 1614 | 84 | 50% | 283 | 103 | 87% | 2.21 |
| Calibri | 32 | 55% | 1575 | 91 | 57% | 277 | 103 | 92% | 2.34 |
| EB Garamond | 32 | 52% | 1542 | 105 | 48% | 312 | 121 | 91% | 1.89 |
| Arial | 31 | 57% | 1592 | 86 | 47% | 270 | 103 | 92% | 2.40 |
| Open Sans | 15 | 56% | 1587 | 75 | 51% | 254 | 90 | 93% | 2.03 |
| Roboto | 13 | 53% | 1557 | 86 | 51% | 269 | 106 | 94% | 1.81 |
| Montserrat | 11 | 42% | 1449 | 90 | 56% | 271 | 108 | 90% | 1.74 |
| Avant Garde | 10 | 37% | 1393 | 105 | 29% | 261 | 90 | 92% | 1.78 |
| Oswald | 10 | 17% | 1155 | 127 | 57% | 295 | 99 | 90% | 1.68 |
| Utopia | 9 | 44% | 1458 | 106 | 45% | 275 | 118 | 84% | 1.77 |
| Lato | 5 | 49% | 1521 | 71 | 52% | 292 | 98 | 92% | 1.70 |
| Poynter Gothic | 4 | 44% | 1470 | 78 | 51% | 266 | 97 | 95% | 1.79 |
| Franklin Gothic | 3 | 27% | 1291 | 87 | 59% | 271 | 108 | 89% | 1.76 |

Fig. 10. Results from our large scale font study. Noto Sans consistently performed highly across preference (highest win rate and Elo Rating). 'Most preferred' refers to the total number of participants for whom the selected font was the absolute favorite. 'Win Rate', 'Average Elo Rating', and 'Elo Disagreement' refer to the toggle-based font preference test. A high disagreement score means participants had highly varying opinions of the font. 'Font Familiarity' was a 5-point Likert scale question from the post-survey (5 = very familiar). 'WPM' and 'Comprehension' refer to the reading effectiveness test. 'Speed Rank' is the percentage of times an individual participant had higher WPM in a given font compared against every other font they read in. Notably, Speed Rank is first computed on an individual participant basis, before being averaged across all participants. The top 6 and bottom 6 fonts according to each metric are color-coded blue and orange, respectively (with darker colors at the extremes).

*6.1.2 Reading speed across all participants.* Taking all participants into account, reading speed differed significantly by passage read, with non-fiction passages read 11.6 WPM faster than fiction ($p = .008$, $R^2_\beta = 0.004$). Self-reported topic familiarity also significantly affected reading speed ($p < .001$ and $R^2_\beta = .002$). Passage topics rated as least familiar to the participant had an average reading speed of 271 WPM, while the highest rated had a speed of 283 WPM. Order of presentation significantly affected reading speed (gaining 1.59 WPM with each subsequent passage, $p < .001$, $R^2_\beta = .002$), as did screen (second screens were read 39 WPM faster than first screens, $p < .001$, $R^2_\beta = .043$). The order of presentation for all passages and fonts was randomly counterbalanced across participants to prevent order effects from confounding outcome measures (see Appendix C). Reading speed decreased significantly with participant age (-1.51 WPM per year, $p < .001$, $R^2_\beta = .019$).

The significant effects found by the LME indicate when reading speed trended in a consistent direction across participants - e.g., despite our efforts to control the difficulty of passage contents, some passages were generally read faster (conversely, slower) across the population. However, font, reading device, and self-reported topic interest were found non-significant by the LME analysis, indicating that for these factors, reading speed did not trend in a consistent direction across the population. Regarding fonts, this means that there is not a set of consistently faster fonts (conversely, slower) across the population as a whole. This result hints at a need for looking into individual differences (Section §6.2) to understand the potential for different fonts to increase speed for different people.

*6.1.3 Reading speed across older participants.* Across the older participants (age $\geq$ 35) we found a similar pattern of results, with the following differences: font was found to significantly affect reading speed ($p = 0.01$, $R^2_\beta = .005$). Notably, the effect of age increased to -2.6 WPM per year ($R^2_\beta = .039$). Figure §11 visualizes reading speed differences between younger and older participants per font. While EB Garamond and Open Sans stand out as the best and worst performers among older participants, the significant effect of font remains even when excluding these fonts from the data. These results suggest that for older participants we can make population-level recommendations, as reading speeds trend in a consistent direction depending on the font. However, as we will discuss in later sections, age is only one factor affecting reading speed. The largest gains in reading speed are evident when someone reads in their more optimal font.

*6.1.4 Reading comprehension.* Reading comprehension scores were relatively flat as the median was 90%, the 25th and 75th quartiles were 85% and 95% respectively, and the minimum score was 70%. Overall, 24% of participants answered all questions correctly. There was minimum variation in scores, so there is lower sensitivity in the hypothesis testing for the comprehension scores. Across all participants, reading comprehension was significantly affected by self-reported topic interest (85.7% correct for passages rated least interesting vs. 93.5% correct for the most interesting; $p < .001$, $R^2_\beta = .019$) and non-fiction content (89.6% comprehension for non-fiction vs. 94.9% for fiction; $p = .013$, $R^2_\beta = .018$), though the passage itself was non-significant. No other factors were significant. Among older participants, topic interest was significant ($p < .001$, $R^2_\beta = .018$), as was non-fiction content (90.4% comprehension for non-fiction vs. 97.1% for fiction; $p = 0.005$, $R^2_\beta = .028$). Additionally, age was significant ($p = .047$, $R^2_\beta = .002$), as was device ($p = .011$, $R^2_\beta = .008$). However, given the lopsided nature of the binary outcome, as well as the lopsided distribution of devices, we urge caution in interpreting the effect of device.

*6.1.5 Takeaways:* Some of the trends that hold across the entire participant population include non-fiction passages being read faster but achieving lower comprehension scores than fiction passages. Topic interest affected comprehension, while topic familiarity affected reading speed. Participants generally read faster as the task progressed, increasing significantly from the first screen in a font to the second screen in the same font and increasing throughout the experiment with each subsequent passage. These results point to a learning effect. Reading slowed down as the age of participants increased, especially after 35 years. Regarding fonts, when considering just the older participants (age $\geq$ 35), we can observe specific fonts affect reading speed, making it possible to provide some initial recommendations for this age group. For instance, EB Garamond and Montserrat were faster fonts on average, while Avant Garde and Open Sans were slow fonts. Someone's age might be one of many factors affecting how fast or slow an individual reader reads with a specific font. For example, across all our participants, fonts do not affect people in the same way, and a font that is effective for one person is not necessarily effective for another person. This observation brings us to our next section, where we scrutinize the individual differences among fonts and participants.

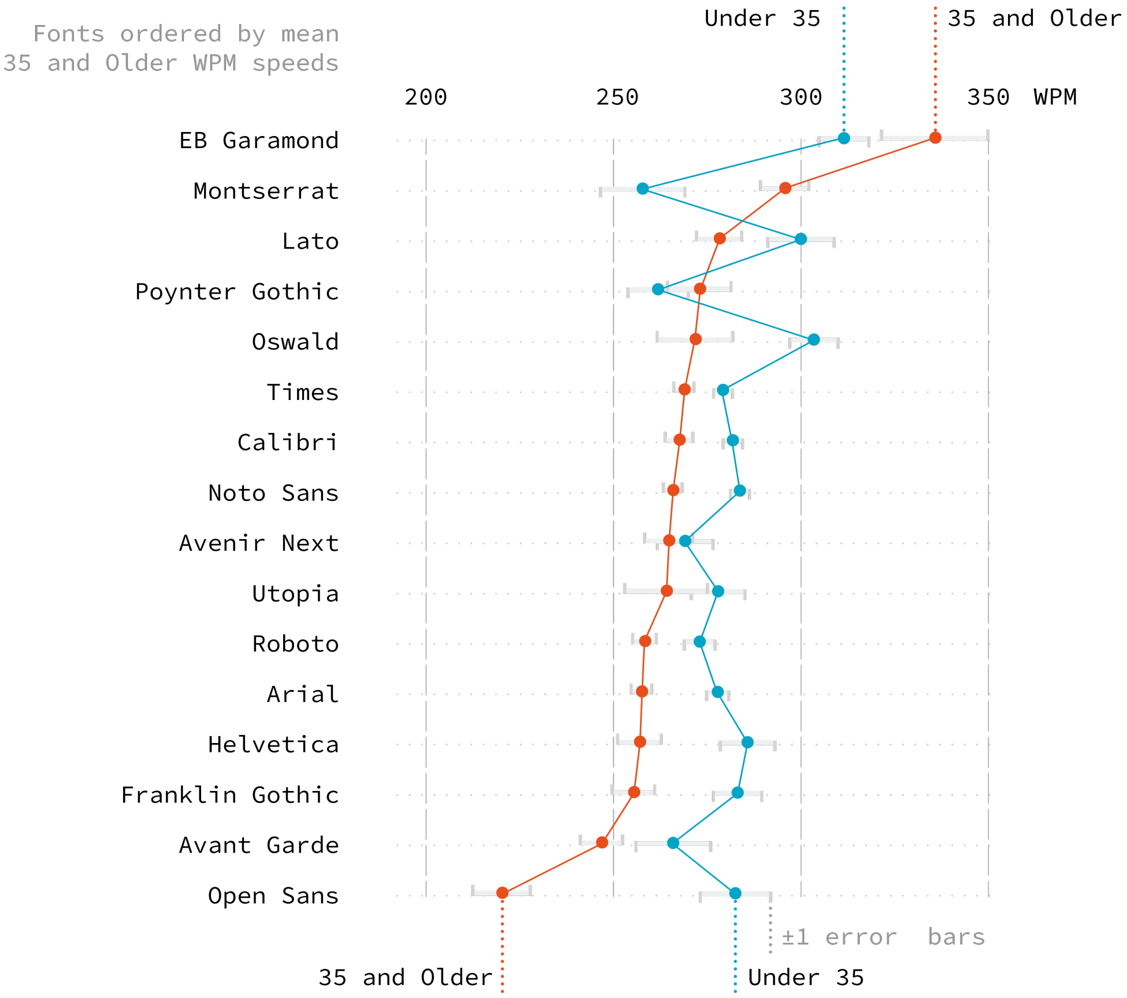


Fig. 11. Mean reading speed (in WPM) per font across participants separated by age, with participants under 35 in blue, and all others in orange. Error bars represent ±1 within-participant standard error. Group sizes vary by font exposure, but total N = 118 for older participants and 234 for younger. Fonts are ordered by mean reading speed within the older group. We see that the younger group read faster on average across many of the fonts, but the older group read faster in EB Garamond and Montserrat.

### 6.2 Individual Differences Results

Results from the population-level analysis demonstrated that while certain factors are more likely to affect participants' reading effectiveness similarly (e.g., non-fiction passages being read faster, on average, than fiction passages) when it came to fonts, different fonts affected the reading speeds of participants in different ways. Moreover, while we could make some initial font recommendations for participants over 35 years, the same could not be said of the population as a whole. This latter finding points to the need to individuate fonts because no single font can benefit all readers.

Importantly, because we observed minimal differences in comprehension scores across participants and removed unreliable WPM measurements (outside of 100–650 WPM), differences in reading speed across fonts do not indicate participants were skimming the material. Instead, they were able to get through it faster while achieving comparable comprehension scores. In other words, the large differences in observed reading speed per individual are due to font (Fig. §12).

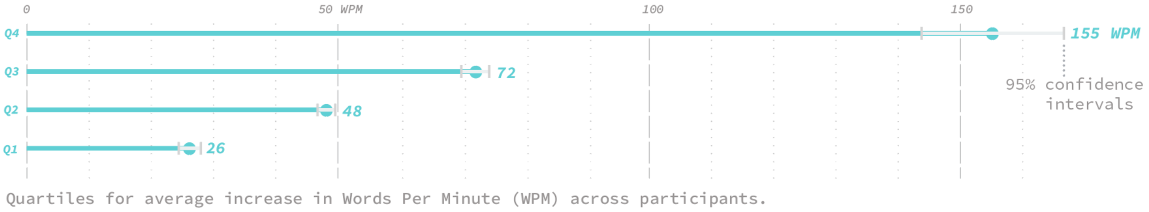


Fig. 12. Participants are divided into quartiles based on their average WPM. This figure shows that the fastest readers also had the biggest gains in reading speed from their slowest to their fastest font, with average improvements in WPM indicated beside each bar. This shows the potential of font to have significant impacts on reading efficiency.

*6.2.1 What gains in reading are achievable by font choice?* At the individual level, there appear to be effective fonts for participants(Fig. §15). Participants read 14% faster in their fastest font (314 WPM, on average) compared to their most preferred font (275 WPM, on average). Most impressively, participants read 35% faster in their fastest font compared to their slowest font (232 WPM, on average) out of the five fonts tested.

To check whether these differences in reading speed are significant and ascribable to the font, we measured the effect size using Cohen's $d$. *Disclaimer:* we are somewhat stretching the applicability of a Cohen's $d$ analysis for this data (given the within-participant analysis, lack of independence, and few data points), so the following results are to be interpreted more of as a rough sanity check. For each participant, we have four reading speed measurements per font[14], since a participant read two different passages in the same font (at two random points in the experiment), with each passage split across two consecutive screens. For each participant, we compare the reading speeds achieved with their individual fastest font to the reading speeds with their slowest font to compute Cohen's $d$. Figure §13 includes a histogram of Cohen's $d$ measurements across all 352 participants, binned by effect size. For 76% of our participants, we found a large effect size (Cohen's $d > 0.8$) of font on reading speed; for 94% of participants, the effect size was medium-large (Cohen's $d > 0.5$). In other words, font choice is indeed driving the effects we are seeing on reading speeds at the individual level.

[14] In some cases, we have fewer than four measurements per participant and font if the reading speeds on particular screens were filtered out as outliers during the data preprocessing; for instance, if the speeds were outside the range of normal reading.

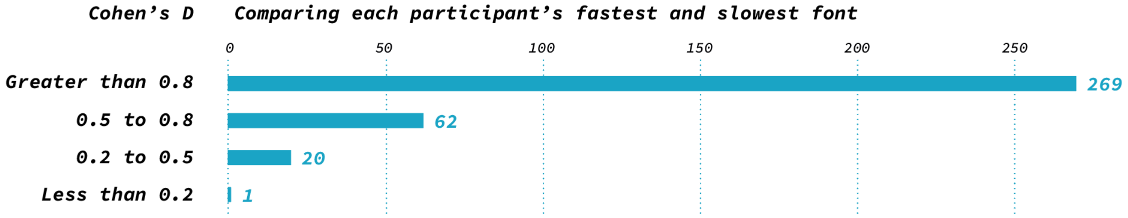


Fig. 13. This histogram bins the effect sizes computed using Cohen's $d$ when comparing the fastest and slowest font per participant. Only 1 participant did not show at least a small effect size when considering reading speed as a function of font.

*6.2.2 Using Speed Rank to interpret Faster Fonts for Individuals:* Since only Times and Noto Sans were read by all participants, we cannot study which fonts were commonly the fastest or slowest across individuals. However, we can focus on the Speed Rank metric (Fig. §10), which compares participants to themselves. The Speed Rank measurements for all of our fonts except for Avant Garde, range from 45% to 59%, indicating there is no single font that all participants read consistently faster with. Among our 16 fonts, there is no scenario where a single font has an exceptionally low Speed Rank yet high average WPM. The Speed Rank for 11/16 fonts ranges from 45% to 52%, indicating that different fonts increase reading speed for different people.

The following results use our Speed Rank metric to help eliminate noise and individual differences by comparing individual participants' achieved reading speeds on pairs of fonts rather than considering absolute reading speeds. Four fonts had the highest Speed Rank, greater than 55%, Franklin Gothic, Calibri, Oswald, and Monsterrat (i.e., they were faster than the other fonts they were compared to more than half the time). Stylistically these four fonts differ greatly (Fig. §3). For example, Monsterrat and Oswald have noticeably different stroke widths. Monsterrat had the tallest x-height among our fonts. In the past, typographers have designed fonts with taller x-heights to increase readability. For example, typographers designed Georgia and Verdana to have a taller x-height than Times New Roman [21]. Oswald and Franklin Gothic, have condensed character spacing, which has been shown to increase reading speed in some studies [11, 100]. Calibri is a familiar font to most, being the default font in Microsoft Word and Excel. Participants might read faster on average in Calibri due to their familiarity with the font. This relationship between font familiarity and speed has been hinted at in previous research [9].

Speed Rank helps explain why relying on averages across a population might not be the most accurate representation of a font's effect on reading speed. It is also an additional metric to help interpret our reading speed results, which do contain some variance due to our between-subjects study design. For example, EB Garamond was the fastest on average at 312 WPM. However, individual participants only read faster in it 48% of the time. This indicates that participants in our study who read using EB Garamond were generally faster readers. Utopia is another font with a lower Speed Rank (45%) despite having a similar average WPM to most other fonts. In contrast, Open Sans was the slowest font on average at 254 WPM, while individual participants read faster in it 51% of the time. Poynter Gothic and Roboto also displayed similar relationships between Speed Rank and average WPM. These discrepancies combined with the large effect sizes reported in this study show the need for the effect of fonts to be studied per individual. It is possible for individuals to experience large gains in reading speed regardless of their baseline speed. In fact, the fastest readers in our study demonstrate the gains possible when reading in their optimal font (Fig. §14).

Of the five fonts, all participants read in Times and Noto Sans as baselines. We observed 87 unique font pairings during the reading speed tests, excluding Times and Noto Sans. However, different pairs had different sampling rates: 38 of these pairs appeared less than five times in our data. In contrast, 3 of the pairs (Arial vs. Calibri, Arial vs. Roboto, and Calibri vs. Roboto) appeared over 100 times each. This probably occurred because the participants generally preferred these fonts. See Tables§20, §21, and §22 in Appendix §J, for the number of observations per font and unique font pairs during the reading speed tests. Due to this uneven sampling of pairs, we can expect some noise in the resulting speed rank measurements. Our study design balanced the study length and amount of conditions we could compare. Future studies can build on our work by focusing on a subset of these fonts and a within-subjects experimental design.

*6.2.3 Which are the highly rated fonts?* Our large study features the first font preference test comparing fonts, normalized by size based on participant perception. Noto Sans and Times were each chosen by 52 (15% of all) participants as the overall winners in the preference tests (Figure §10, 'Most Preferred'), with Avenir Next, Helvetica, Calibri, EB Garamond, and

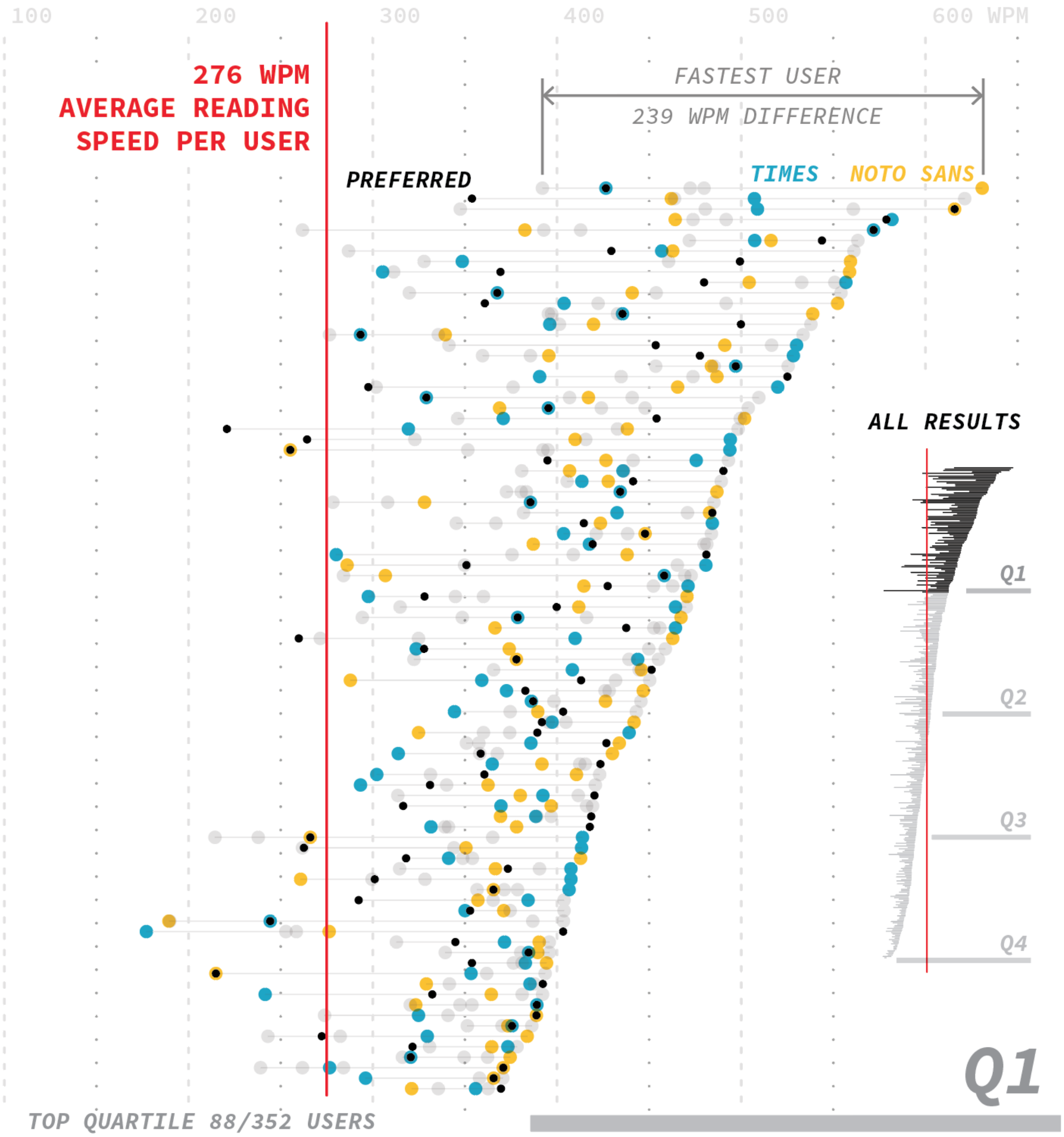


Fig. 14. The fastest readers (top quartile) show the potential that a single manipulation, font, can have on reading speed. Each row represents one participant, with the reading speeds achieved in 5 different fonts plotted as color-coded circles: preferred font (black), Times (blue), Noto Sans (yellow), and another 2–3 randomly-selected fonts (grey). On the left-most of the figure are the slowest fonts for each participant, and on the right are the fastest. The horizontal distance between the two ends is the speed increase achievable by manipulating font. There is no one font or manipulation (preference) that can determine an individual's fastest font.

Arial also performing favorably according to the preference metrics. Nevertheless, every single font was the preferred font of at least 3 participants. This points to considerable diversity in font preferences across individuals.

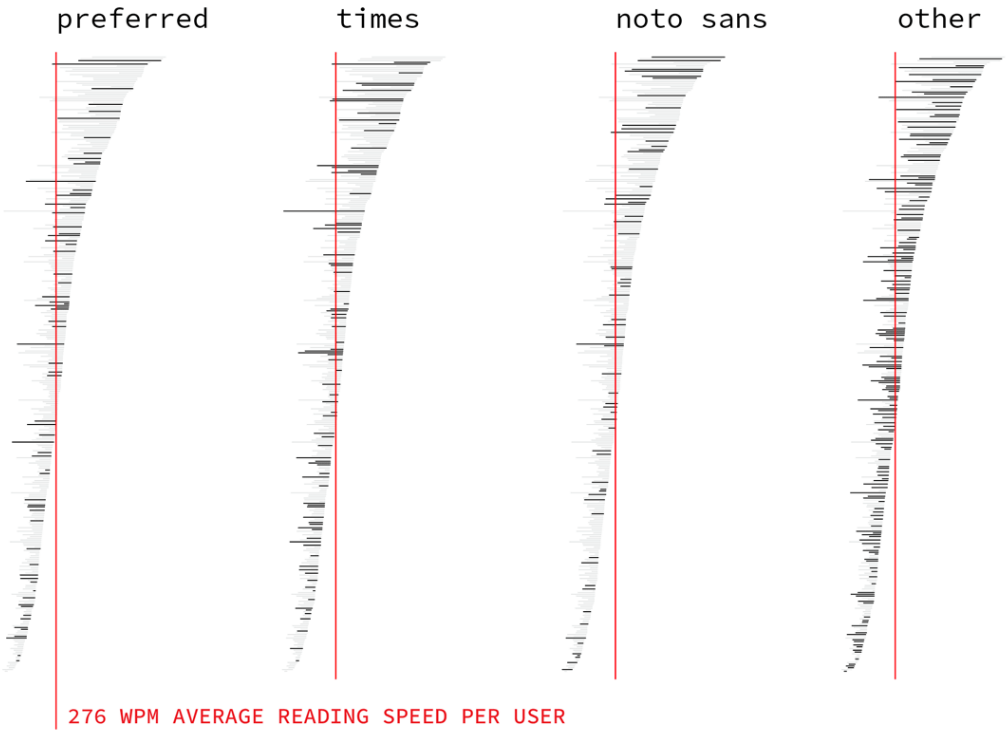


Fig. 15. This figure contains another view of the data from Fig. §14, zoomed out and replicated four times to show that different participants read fastest using different fonts. The label at the top of each plot is one of the study's conditions for reading speed: a participant's most preferred font, Noto Sans, Times, and 'other' contains the other fonts participants read in. Highlighted with a black line are all the participants for which the labeled font was the fastest. For example, each black horizontal line in "preferred" corresponds to a participant whose most preferred font was their fastest. In the next two plots, we highlight participants whose fastest fonts were Times and Noto Sans, respectively. The length of each line corresponds to the speed increase between a participant's slowest and fastest fonts. Participants are sorted by their max reading speeds (fastest readers up top).

Another indication of diversity in preferences are the inter-participant disagreement scores (Figure §10, 'Elo Disagreement'). For instance, while Times and EB Garamond were highly rated fonts overall, they split opinions across participants, some of which consistently voted them up (correspondingly, down) in the preference tests. On the other hand, Open Sans was generally likable based on its pairwise font comparisons and the low inter-participant disagreement scores.

Controlling for size generally led to smaller fonts (Times, EB Garamond, Helvetica, Calibri) performing consistently better than in our previous study [107]. As a notable example, Times, which was in the bottom 5 fonts according to Elo Rating in our previous study, is in the top 5 fonts in the present study. In contrast, participant preferences for Noto Sans were relatively stable across both studies. It was in the top 5 fonts for 80% of participants in our previous study and 77% of participants in the present study. Overall, with the highest win rate and average Elo Rating, it was the most preferred font.

As in our previous study, familiarity was not predictive of font preference. Participants were familiar with their recommended font only 52% of the time. Pearson's Correlation shows only a small effect between font familiarity and Elo Rating per participant ($r = 0.18$, $p < 0.05$). The most preferred font, Noto Sans, was also among the least familiar fonts to participants.

Please refer to Appendix §I for additional results on how dwell time and font familiarity affect a participant's font preferences.

*6.2.4 Is people's preferred font their most effective font?* Our study explicitly considers effectiveness, measured using WPM and comprehension. However, since comprehension is relatively flat, we look at reading speed only. Overall, participants read the fastest in their most preferred font 20% of the time, but they also read the slowest in their preferred font 20% of the time (out of five total fonts tested per participant), which is precisely at chance level. They also read in their preferred font at an average WPM.

Participants read faster in their most preferred fonts than in Times 50% of the time, and faster than in Noto Sans 51% of the time. In other words, participants do no better or worse, on average, by reading in their preferred font. These findings run contrary to participants' beliefs: 73% of participants believed their most preferred font would also be their most effective font to read in. Times and Noto Sans, which were generally preferred fonts, were not consistently effective fonts across participants. Prior work has shown a similar dissociation between preference and reading speed. For instance, Boyarski et al. found that while participants expressed a preference for Verdana, they read faster with Georgia [21]. Our work builds on this prior finding by studying and reproducing this relationship across a much wider collection of fonts.

*6.2.5 Takeaways:* We found that different fonts are effective for different people, leading us to believe that custom reading experiences can help people read more effectively. Nevertheless, some fonts, including EB Garamond and Montserrat, tend to increase the reading speeds of readers older than 35 years. For other decisions on font choice, please refer to Fig. §10, which includes some performance metrics across all the fonts in our study. For instance, Noto Sans, Times, and Calibri performed quite highly on preference and effectiveness (reading speed and comprehension). Importantly, there was not a single font that increased reading speed for everyone. Our results show a considerable spread in both preference and effectiveness for specific fonts across individuals. Furthermore, our results indicate that neither preference nor familiarity with a font can predict reading speed. Despite this, we witnessed a 35% increase in reading speed, on average, when comparing a participant's fastest font to their slowest font of the five individual fonts tested.

## 7 DISCUSSION

### 7.1 Takeaways

Here we summarize the takeaways for the investigations presented in this paper.

- Our results show that some fonts, including EB Garamond and Montserrat, tend to increase the reading speeds of readers older than 35 years, on average; however, such recommendations can not be made for the general population.
- While fonts and typographic considerations generally matter more for older participants, starting at age 35 in our data, we observe larger reading speed gains when accounting for individual differences per font per participant.
- Different fonts are effective for different people, leading us to believe that custom reading experiences can help people read more effectively. By designing tools to match individuals to their best font, individual readers can experience large gains in reading speed.
- Preference ≠ effectiveness. People do not know what is good for them in terms of font choice for reading.
- Preference for fonts is personal. People differ in what they prefer.
- Familiarity with a font does not drive preference, and has a small effect on reading speed. A font need not be chosen for an application just because people may be used to seeing it.
- A single size does not fit all fonts. If an application has a few font options for the same piece of text, then each font needs to be adjusted in size according to the font's characteristics.
- When normalizing fonts based on font attributes, x-height is not the only option, nor was it the most common option selected based on participant perception.

### 7.2 Towards Individuated Reading Experiences

Instantaneous reader improvement is the promise of good information design [12, 45, 52, 115]. Information design, the process of optimally formatting the elements of the page to convey information, has historically been relegated to professional practitioners designing for everyone. This is because publishing technologies have historically focused on publishing one document in one format. While it may be simpler to provide everyone a slight boost in performance, individuating or personalizing participant experiences can augment human performance even more. Our results indicate fonts exist that can help readers above the age of 35 read faster. However, the idea that finding the fastest font per individual shows more promise for participants regardless of their age. The large effect sizes per person we report point to the potential for personalized reading experiences to help participants overcome the ever-growing burden of information overload. Information design can affect different areas of our lives, from understanding financial documents to voter registration or even reading for pleasure.

Reading technologies are presently shifting control of information format, shifting it from publisher to reader. Microsoft's Immersive Reader[15] allows the abstracting and reformatting of all text on a webpage [61]. E-book technologies include options to reflow typographic and page design in the moment. Now, even historically static digital documents are receiving similar capabilities. Adobe Acrobat Reader using Liquid Mode can reflow a PDF to the desired format, even for scanned, optical character recognition (OCR) enriched documents, potentially allowing the entirety of the written word to be flexibly reformatted to suit the needs of the reader [51]. However, this growing ability for applications such as Liquid Mode or Mozilla Firefox's Reader View to automatically reflow text does not allow them to manipulate text based on the reader's needs [57]. Efficient evidence-based matching of the reader to specific fonts is a scientific and technological challenge. Future research should develop innovations to help match people with their most effective font, similar to matching someone with their most effective prescription to improve their vision.

Our results indicate that readers' preferences do not predict their fastest fonts to read in. If someone does not know what they need, perhaps a system could provide it. In our work, familiarity or preference with specific formats had a limited effect on reading speed. There is also no one-size-fits-all solution that emerged to improve reading speed for all readers. Matching a reader to information design that can deliver substantial benefit is presently time-consuming, and no theoretical or computational model exists to assist. Happily, studies with a large participant pool point to how to leverage a big data approach to resolve the individuation challenge rapidly, as previously successfully undertaken in high individual difference contexts such as voice and handwriting recognition [1, 60, 90]. Theoretical foundations will be essential to this approach, and we find the beginnings of these in existing legibility, readability, communication, and vision science work [48, 93, 107, 108, 117]. Computational models will likewise be necessary, and what little work exists here provides useful foundations for the geometry, if not the utility, of fonts and typography [9, 55, 101, 114].

Our results provide evidence for font's vital importance to readability and provide a possibility to help reduce information overload. Our results show the potential importance of individuation to improve reading speed. Building on prior work, we can confidently recommend that tailoring content to each reader will ultimately improve readability for all. Secondly, our results show that age might be an essential factor to consider when individuating font choice to increase reading speed. Third, we built a new understanding of the role of preference, which does not impact effectiveness but is personal and underscores the need for individuation. Fourth, we provide a new method to rethink size normalization between fonts based on human perception. However, there is a growing need for new research at the intersection of these contributions. Our results do not cover every possible font combination or multiplicative sets of design manipulations per font when considering additional participant demographics and languages. Researching this information design space will require collecting additional data

[15] https://education.microsoft.com/en-us/resource/9b010288

to create new theoretical and computational models for individuating design. Understanding what individual factors drive beneficial information design could deliver new impacts to reduce information overload.

### 7.3 Limitations and Future Work

*Participants:* While we intended for the paid crowdworkers recruited for our main study to act as a general population sample, our participants' demographics (particularly ages) might not be entirely representative for several reasons. First, the age distributions of our participants closely resemble those of the digital reading population, see Section§5.1.4. Second, prior research shows that paid crowdworkers on Amazon's Mechanical Turk are more diverse than standard Internet and American college samples [22], and sample composition varies dynamically based on study topic, task complexity, recruitment materials, and the time of day the study is made available [73]. One approach to increase the diversity of the sample is to recruit participants from multiple crowdsourcing platforms such as Prolific, Crowdflower, and UserTesting and potentially supplement with unpaid voluntary participation [53, 57, 106, 109, 110]. In addition, only 0.4% of our participants had less than a high school education compared to the national average of 9.8% for people age 18 and over, see Table §1 in Appendix§F. Future work should address these populations that were difficult to recruit in our remote opt-in readability studies.

Our paid crowdworkers specifically chose to participate in our readability studies. This self-selection bias may leave out participants who are not interested in reading or improving their reading. Most of our participants were in their 20s and 30s, and we specifically excluded participants who reported any learning or reading disabilities (due to small samples). Because age and ability differences may exert some of the strongest effects on reading outcomes [8, 10, 37], we recommend more targeted recruiting, to systematically increase the number of samples at different age ranges. In the future, our reading studies can be extended to additional specialized populations to evaluate our results' generalization in cases where the most significant effects of font choice may be achieved.

*Language:* Our reading passages are in English, and data only includes participants who self-reported being comfortable reading English, while being located in the US. Thus, our results are not cross-cultural. Future work could extend our methods to study how font and language can affect readability in different languages, as well as looking at second language learners. Such efforts will require (sourcing or creating) a new set of properly leveled reading materials with corresponding comprehension questions, which in our experience was the biggest initial barrier to running readability studies.

*Controlling for Visual Font Size:* A limitation of conducting our remote readability studies is the variations in the physical size of screens across devices, participants' visual angle, and varying font size across monitor types. Prior in-lab readability research used consistent monitor sizes, and they also used smaller point sizes for fonts because the pixel densities of physical monitors were lower than they are now. For example, the visual size of fonts rendered at 10-point size in studies in the late 1990s and early 2000s will look smaller on today's monitors [13, 21]. Our remote readability methods trade the internal validity of in-lab studies by studying readers in their everyday reading environments. Prior work has suggested controlling for participants' visual angle or stimuli for remote readability studies on desktops [8, 120]. Another recent method to control for viewing distance on desktops is the virtual chinrest [56]. We did not consider these methods because we wanted to recruit participants regardless of their intended reading device. We also wanted to provide the reader the agency to behave naturally, similar to Chatrangsan et al. [28]. Ideally, future work could manipulate font size per participant to ensure the physical font size is similar across all reading experiences and devices.

*Font Familiarity:* A participant's familiarity with specific fonts is challenging to test. We showed participants all 16 fonts used in the study and asked them to self-report their familiarity with each using a Likert scale. Since each font name was rendered in its own font, it is not clear whether participants indicated their familiarity with the font's name or its visual appearance. Future work should address the subtle relationships between participants and their familiarity with, recognizability, and everyday exposure to specific fonts.

*Measures of reading speed:* Our calculation of reading speed was based on when participants clicked to move to the next study screen. While we took measures to only capture data points that fell within the target range of expected reading speeds, our calculation is rough and can introduce noisy data. Future remote studies can consider eye movements or voice recordings for more precise reading speed estimates but will need to evaluate how these additional measurements might interfere with natural reading. Suppose future studies want to focus on reading speed. In that case, we recommend using easier passages, for example, 8th-grade level reading passages, since using more difficult passages can introduce a speed and comprehension trade-off [105].

*Choice of fonts:* Post-hoc discussions with a typographer revealed nuances regarding font comparisons. Specifically, not all of our study fonts were designed to display body text on digital devices. For instance, Franklin Gothic was designed for printing newspapers, Oswald is a popular font for headings, and Noto Sans was specifically optimized for reading on digital devices with small screens. For a fair comparison, future studies can specifically consider fonts optimized for digital devices.

*Variable fonts:* Our work compares fonts that differ among multiple properties, including stroke weight, character width, and optical size. To remove the confounding effects of size, we individually re-normalized all fonts to a standard perceptual size. In the future, rather than comparing entirely different font families, variable fonts can offer more fine-grained control over the weight, width, and optical size parameters of a font. This study design choice creates opportunities to study the anatomical differences of sans and sans-serif, humanist vs. geometric fonts in isolation of other confounding factors. Also, variable fonts would allow researchers to measure how fine-grained adjustments to the x-height, ascender, or descender individually contribute to effectiveness.

*Reading formats:* In studying fonts, there are multiple factors to control for. Future work could investigate additional format differences beyond font, including character and line spacing, letter spacing, and stroke width. All of these various font attributes could contribute to a perceived information density. As aforementioned, we recommend using variable fonts to enable an analogous comparison of weight, width, and optical size. This focus on variable fonts will enable experiments to determine what anatomical parameters (category, classification, weight, width, or optical size) contribute to effectiveness, preference, and familiarity.

*Within-Subjects Study Design:* Our goal was to study as many fonts as possible within a remote setting. While Speed Rank provides a valuable metric to help provide different interpretations to our results, a within-subjects design provides stronger analysis methods. Our pilot studies show that having a single participant read in all 16 fonts in a remote setting is not advisable. Our pilot studies evaluated how behaviors were affected when participants read six or eight fonts after completing the preference test. Participants were more likely to abandon the test in these pilot studies, and their reading speed measurements dropped noticeably during the final reading rounds. Our current between-subjects design for reading speed showed this drop-off did not occur, thus adding validity to our results. However, because font preference does not predict effectiveness, even when controlling for font size, we believe a within-subjects study design is more appropriate to study reading speed differences in remote readability studies.

## 8 CONCLUSION

This work presented the first large-scale remote readability study considering font's impact on Interlude Reading performance, measured by words per minute and comprehension. Our remote study design exchanges internal validity for applied validity by evaluating participants reading in their naturalistic environments while controlling for font size based on human perception. Based on evidence from our prior study that participants preferred fonts related to perceived size, we normalized font size using a novel size normalization approach. Even with font size normalization, we found that font preference does not drive effectiveness, despite participants believing it does. While we found initial evidence that specific fonts might help readers over 35 years, the main takeaway is that different fonts work best for different people. Finding the best font for an individual is an open question worth exploring.

There is an extensive amount of excellent readability research focusing on reading on digital devices from the past two decades. Prior research has made recommendations for future work to overcome the challenges of conducting digital readability studies ranging from recruiting larger or more diverse participant pools [17, 19, 28, 86], to selecting a larger or more diverse set of fonts [16, 86, 88], to studying reading behaviors in the real world [9, 57, 111]. While our work incorporates a number of these recommendations, future work is still needed to overcome our methods' limitations.

Over time prior studies have agreed and disagreed with each other's results, see Figure §16 in the Appendix. For example, our work and most prior research have found that font choice and aspects of font size affect participants' preferences [16, 28, 31, 86, 107]. In contrast, there is a paper that did not replicate this finding [19]. Some researchers have also found that font choice effects reading speed [5, 6, 28, 86] while others have not [16, 17, 21, 107]. Prior research is also split on the relationship between font size and reading speed, with some work showing that font size does affect reading speed [6, 16, 28, 88] while others work showing it does not [17, 19, 31]. Even Boyarski et al.'s seminal study found mixed results when comparing different factors [21]. It is possible to attribute the cause of these contradictions to a multitude of factors ranging from the ever-evolving font choices, device types, demographics, and digital technologies. We believe these contradictions do not invalidate any one research result. Instead, they reinforce the complexity inherent in studying digital readability. This observation provides further evidence that reading experiences need to be individuated to help as many readers as possible. We hope that future researchers can expand on our remote readability methods to improve their internal validity and compare their results directly and empirically with in-person methods.

Our pattern of findings highlights an opportunity to augment reading speed for individual adult readers through different font choices. In comparison to participants' average reading speed, the average reader in our study could add 38 words a minute by changing their font. This increase is equivalent to an additional four to five pages an hour given 500-words per page. When comparing a participant's fastest font to their average reading speed, participants in the top quartile for the delta added 79 WPM, or nine to ten pages an hour. In both cases, average comprehension remains similar and high. In the context of Interlude Reading, this gain shows individual readers could consume more information in limited windows. For example, suppose a news article, journal, or forum post is roughly 700 words, requiring around two minutes for an average reader. For this hypothetical document length, an individual could read it 24% faster in their most effective font while retaining normal reading comprehension levels. A reader could use these 30 seconds saved to read comments or look at related posts. Social media companies, which thrive on the volume of interaction, might find font as one mechanism to increase interactions. Our results point to a future where individuation can boost reading speed for readers of various ability levels, showing the potential to enhance readability for all.

The transformation of reading by digital devices is at the heart of our work and dictates the subsequent work necessary. The high variability seen in our studies represents both a challenge and an opportunity. While there is clear potential for improvement, understanding how to help each individual in various reading contexts and tasks is unsolved, requiring new collaborations and tools to solve. The potential impacts on individual reading efficacy highlighted here point to a future where machines can help readers attain their full reading potential. We hope the present reader and the multidisciplinary communities will continue to perform this work. Let us engineer better reading for everyone.

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## REFERENCES

[1] Christoph Amma, Marcus Georgi, and Tanja Schultz. 2014. Airwriting: a wearable handwriting recognition system. *Personal and ubiquitous computing* 18, 1 (2014), 191–203.

[2] Aries Arditi. 2004. Adjustable typography: an approach to enhancing low vision text accessibility. *Ergonomics* 47, 5 (2004), 469–482.

[3] Dana Bachmann and Paul Holdsworth. 2016. DVV International: The new Skills Agenda for Europe. https://www.dvv-international.de/en/adult-education-and-development/editions/aed-832016-skills-and-competencies/section-1-agenda-setting/the-new-skills-agenda-for-europe/. (Accessed on 01/02/2021).

[4] Justin Baer, Mark Kutner, John Sabatini, and Sheida White. 2009. Basic Reading Skills and the Literacy of America's Least Literate Adults: Results from the 2003 National Assessment of Adult Literacy (NAAL) Supplemental Studies. NCES 2009-481. *National Center for Education Statistics* (2009), 1–83.

[5] Rachel V Ball, Dave B Miller, Shaun Wallace, Kathlyn Camargo Macias, Mahmoud Ibrahim, Ernesto Robalino Gonzaga, Olga Karasik, Dekai R Rohlsen-Neal, Sarah Barrientos, Edward A Ross, et al. 2021. Optimizing Electronic Health Records Through Readability. In *Proceedings of the International Symposium on Human Factors and Ergonomics in Health Care*, Vol. 10. Sage Publications Sage CA: Los Angeles, CA, Los Angeles, CA, USA, 65–70.

[6] Jayeeta Banerjee, Deepti Majumdar, Madhu Sudan Pal, and Dhurjati Majumdar. 2011. Readability, subjective preference and mental workload studies on young indian adults for selection of optimum font type and size during onscreen reading. *Al Ameen Journal of Medical Sciences* 4, 2 (2011), 131–143.

[7] Sofie Beier. 2009. *Typeface legibility: towards defining familiarity*. Ph.D. Dissertation. Royal College of Art.

[8] Sofie Beier, Sam Berlow, Esat Boucaud, Zoya Bylinskii, Tianyuan Cai, Jenae Cohn, Kathy Crowley, Stephanie L Day, Tilman Dingler, Jonathan Dobres, et al. 2021. Readability Research: An Interdisciplinary Approach. *arXiv preprint arXiv:2107.09615* (2021).

[9] Sofie Beier and Kevin Larson. 2013. How does typeface familiarity affect reading performance and reader preference? *Information Design Journal* 20, 1 (2013), 16–31.

[10] Sofie Beier and Chiron AT Oderkerk. 2019. The effect of age and font on reading ability. *Visible Language* 53, 3 (2019), 50–68.

[11] Sofie Beier, Chiron AT Oderkerk, Birte Bay, and Michael Larsen. 2021. Increased letter spacing and greater letter width improve reading acuity in low vision readers. *Information Design Journal* (2021).

[12] Dirk Bergemann and Stephen Morris. 2019. Information design: A unified perspective. *Journal of Economic Literature* 57, 1 (2019), 44–95.

[13] Michael Bernard, Chia Hui Liao, and Melissa Mills. 2001. The effects of font type and size on the legibility and reading time of online text by older adults. In *CHI'01 extended abstracts on Human factors in computing systems*. ACM, ACM, New York, NY, USA, 175–176.

[14] Michael Bernard, Bonnie Lida, Shannon Riley, Telia Hackler, and Karen Janzen. 2002. A comparison of popular online fonts: Which size and type is best. *Usability news* 4, 1 (2002), 2002.

[15] Michael Bernard and Melissa Mills. 2000. So, what size and type of font should I use on my website. *Usability news* 2, 2 (2000), 1–5.

[16] Michael L Bernard, Barbara S Chaparro, Melissa M Mills, and Charles G Halcomb. 2003. Comparing the effects of text size and format on the readibility of computer-displayed Times New Roman and Arial text. *International Journal of Human-Computer Studies* 59, 6 (2003), 823–835.

[17] David Beymer, Daniel Russell, and Peter Orton. 2008. An eye tracking study of how font size and type influence online reading. In *Proceedings of the 22nd British HCI Group Annual Conference on People and Computers: Culture, Creativity, Interaction-Volume 2*. BCS Learning & Development Ltd., Swindon, United Kingdom, 15–18.

[18] David Beymer and Daniel M Russell. 2005. WebGazeAnalyzer: a system for capturing and analyzing web reading behavior using eye gaze. In *CHI'05 extended abstracts on Human factors in computing systems*. ACM, ACM, New York, NY, USA, 1913–1916.

[19] Sanjiv K Bhatia, Ashok Samal, Nithin Rajan, and Marc T Kiviniemi. 2011. Effect of font size, italics, and colour count on web usability. *International journal of computational vision and robotics* 2, 2 (2011), 1–26.

[20] Laura Bix. 2002. The elements of text and message design and their impact on message legibility: A literature review. *Journal of Design Communication* 4 (2002), 1–15.

[21] Dan Boyarski, Christine Neuwirth, Jodi Forlizzi, and Susan Harkness Regli. 1998. A study of fonts designed for screen display. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. ACM Press/Addison-Wesley Publishing Co., ACM, New York, NY, USA, 87–94.

[22] Michael Buhrmester, Tracy Kwang, and Samuel D Gosling. 2016. Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality data? (2016).

[23] US Census Bureau. [n.d.]. Educational Attainment in the United States: 2020. https://www.census.gov/data/tables/2020/demo/educational-attainment/cps-detailed-tables.html. (Accessed on 09/19/2021).

[24] Ivan Burmistrov, Tatiana Zlokazova, Iuliia Ishmuratova, and Maria Semenova. 2016. Legibility of light and ultra-light fonts: Eyetracking study. In *Proceedings of the 9th Nordic Conference on Human-Computer Interaction*. ACM, ACM, New York, NY, USA, 110.

[25] Ronald P Carver. 1990. *Reading rate: A review of research and theory.* Academic Press, Cambridge, MA, USA.

[26] Ronald P Carver. 1992. Reading rate: Theory, research, and practical implications. *Journal of Reading* 36, 2 (1992), 84–95.

[27] Pew Research Center. 2012. Younger AmericansâĂŹ Reading and Library habits | Pew Research Center. https://www.pewresearch.org/internet/2012/10/23/younger-americans-reading-and-library-habits/. (Accessed on 10/01/2021).

[28] Maneerut Chatrangsan and Helen Petrie. 2019. The effect of typeface and font size on reading text on a tablet computer for older and younger people. In *Proceedings of the 16th Web For All 2019 Personalization-Personalizing the Web*. ACM, ACM, New York, NY, USA, 5.

[29] Kathy Crowley and Marjorie Jordan. 2019. Base Font Effect on Reading Performance - Readability Matters. https://readabilitymatters.org/articles/font-effect. (Accessed on 09/19/2019).

[30] Kathy Crowley and Marjorie Jordan. 2019. Readability Formats Offer Instantaneous Change - Readability Matters. https://readabilitymatters.org/articles/instantaneous-change. (Accessed on 09/20/2019).

[31] Iain Darroch, Joy Goodman, Stephen Brewster, and Phil Gray. 2005. The effect of age and font size on reading text on handheld computers. In *IFIP conference on human-computer interaction*. Springer, Springer, New York, NY, USA, 253–266.

[32] Nediyana Daskalova, Eindra Kyi, Kevin Ouyang, Arthur Borem, Sally Chen, Sung Hyun Park, Nicole Nugent, and Jeff Huang. 2021. Self-E: Smartphone-Supported Guidance for Customizable Self-Experimentation. *Work* 1145 (2021), 3411764–3445100.

[33] Bill Davis. 2004. Fonts on the front page. A study of typefaces on the front pages of AmericanâĂŹs top newspapers. *Chicago: Ascender Corporation* (2004).

[34] Joshua R De Leeuw. 2015. jsPsych: A JavaScript library for creating behavioral experiments in a Web browser. *Behavior research methods* 47, 1 (2015), 1–12.

[35] Joshua R de Leeuw and Benjamin A Motz. 2016. Psychophysics in a Web browser? Comparing response times collected with JavaScript and Psychophysics Toolbox in a visual search task. *Behavior Research Methods* 48, 1 (2016), 1–12.

[36] David DiSalvo. 2012. Who Reads the Most in the US? The Answer Might Surprise You. https://www.forbes.com/sites/daviddisalvo/2012/10/23/who-reads-the-most-in-the-us-the-answer-might-surprise-you/?sh=70617c6528b2. (Accessed on 10/01/2021).

[37] Jonathan Dobres, Nadine Chahine, Bryan Reimer, David Gould, Bruce Mehler, and Joseph F Coughlin. 2016. Utilising psychophysical techniques to investigate the effects of age, typeface design, size and display polarity on glance legibility. *Ergonomics* 59, 10 (2016), 1377–1391.

[38] Jonathan Dobres, Bryan Reimer, and Nadine Chahine. 2016. The effect of font weight and rendering system on glance-based text legibility. In *Proceedings of the 8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*. ACM, ACM, New York, NY, USA, 91–96.

[39] Jonathan Dobres, Benjamin Wolfe, Nadine Chahine, and Bryan Reimer. 2018. The effects of visual crowding, text size, and positional uncertainty on text legibility at a glance. *Applied ergonomics* 70 (2018), 240–246.

[40] Robert L Duchnicky and Paul A Kolers. 1983. Readability of text scrolled on visual display terminals as a function of window size. *Human Factors* 25, 6 (1983), 683–692.

[41] Lloyd J Edwards, Keith E Muller, Russell D Wolfinger, Bahjat F Qaqish, and Oliver Schabenberger. 2008. An R2 statistic for fixed effects in the linear mixed model. *Statistics in medicine* 27, 29 (2008), 6137–6157.

[42] Arpad E Elo. 1978. *The rating of chessplayers, past and present*. Arco Pub.

[43] Martin J Eppler and Jeanne Mengis. 2008. The concept of information overload-a review of literature from organization science, accounting, marketing, mis, and related disciplines (2004). *Kommunikationsmanagement im Wandel* (2008), 271–305.

[44] James Gareth, Witten Daniela, Hastie Trevor, and Tibshirani Robert. 2013. *An introduction to statistical learning: with applications in R*. Springer, New York, NY, USA.

[45] Lisa Graham. 2012. *Basics of design: Layout & Typography for beginners*. Cengage Learning.

[46] Shengbo Guo and Scott Sanner. 2010. Real-time multiattribute bayesian preference elicitation with pairwise comparison queries. In *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics*. JMLR Workshop and Conference Proceedings, Microtome Publishing, Brookline, MA, USA, 289–296.

[47] Severin Hacker and Luis Von Ahn. 2009. Matchin: eliciting user preferences with an online game. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, ACM, New York, NY, USA, 1207–1216.

[48] Daniel Hannon, Esa Rantanen, Ben Sawyer, Raymond Ptucha, Ashley Hughes, Katherine Darveau, and John D Lee. 2019. A Human Factors Engineering Education Perspective on Data Science, Machine Learning and Automation. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, Vol. 63. SAGE Publications Sage CA: Los Angeles, CA, SAGE Publications, Los Angeles, CA, USA, 488–492.

[49] Ralf Herbrich, Tom Minka, and Thore Graepel. 2006. TrueSkillâĎć: a Bayesian skill rating system. In *Proceedings of the 19th international conference on neural information processing systems*. ACM, New York, NY, USA, 569–576.

[50] Chien-Ju Ho, Aleksandrs Slivkins, Siddharth Suri, and Jennifer Wortman Vaughan. 2015. Incentivizing high quality crowdwork. In *Proceedings of the 24th International Conference on World Wide Web*. ACM, New York, NY, USA, 419–429.

[51] Adobe Inc. 2020. Enhancing PDF readability with Liquid Mode: Mobile-friendly PDFs through AI, ML & UX design. https://blog.adobe.com/en/2020/10/12/making-pdfs-mobile-friendly-ai-powered-liquid-mode.html. (Accessed on 03/21/2021).

[52] Robert E Jacobson and Robert Jacobson. 1999. *Information design*. MIT press, Cambridge, MA, USA.

[53] Warut Khern-am nuai, Karthik Kannan, and Hossein Ghasemkhani. 2018. Extrinsic versus intrinsic rewards for contributing reviews in an online platform. *Information Systems Research* 29, 4 (2018), 871–892.

[54] Mark Kutner, Elizabeth Greenberg, and Justin Baer. 2006. A First Look at the Literacy of America's Adults in the 21st Century. NCES 2006-470. *National Center for Education Statistics* (2006).

[55] Kevin Larson and Matthew Carter. 2016. Sitka: a collaboration between type design and science. In *Digital Fonts and Reading*. World Scientific, Singapore, 37–53.

[56] Qisheng Li, Sung Jun Joo, Jason D Yeatman, and Katharina Reinecke. 2020. Controlling for participantsâĂŹ viewing distance in large-scale, psychophysical online experiments using a virtual chinrest. *Scientific reports* 10, 1 (2020), 1–11.

[57] Qisheng Li, Meredith Ringel Morris, Adam Fourney, Kevin Larson, and Katharina Reinecke. 2019. The impact of web browser reader views on reading speed and user experience. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. ACM, New York, NY, USA, 1–12.

[58] Andrew Mao, Ece Kamar, Yiling Chen, Eric Horvitz, Megan E Schwamb, Chris J Lintott, and Arfon M Smith. 2013. Volunteering versus work for pay: Incentives and tradeoffs in crowdsourcing. In *First AAAI conference on human computation and crowdsourcing*. AAAI, Menlo Park, CA, USA, 94–102.

[59] Pedro AS Matos and Regina Delfino. 2014. Newspaper Design Contributions for Sustainable Development. In *46th Annual International Conference of the International Circle of Educational Institutes for Graphic Arts: Technology and Management, Athens and Corinthia: Greece*. International Circle, Stuttgart, Germany.

[60] Ian McGraw, Rohit Prabhavalkar, Raziel Alvarez, Montse Gonzalez Arenas, Kanishka Rao, David Rybach, Ouais Alsharif, Haşim Sak, Alexander Gruenstein, Françoise Beaufays, et al. 2016. Personalized speech recognition on mobile devices. In *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, IEEE, Piscataway, NJ, USA, 5955–5959.

[61] Katherine McKnight. 1996. Leveling the playing field with Microsoft learning tools.

[62] Gail McKoon and Roger Ratcliff. 2016. Adults with poor reading skills: How lexical knowledge interacts with scores on standardized reading comprehension tests. *Cognition* 146 (2016), 453–469.

[63] Brett Miller, Peggy McCardle, and Ricardo Hernandez. 2010. Advances and remaining challenges in adult literacy research. *Journal of learning Disabilities* 43, 2 (2010), 101–107.

[64] Aliaksei Miniukovich, Antonella De Angeli, Simone Sulpizio, and Paola Venuti. 2017. Design guidelines for web readability. In *Proceedings of the 2017 Conference on Designing Interactive Systems*. ACM, ACM, New York, NY, USA, 285–296.

[65] Aliaksei Miniukovich, Michele Scaltritti, Simone Sulpizio, and Antonella De Angeli. 2019. Guideline-Based Evaluation of Web Readability. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. ACM, ACM, New York, NY, USA, 508.

[66] Meredith Ringel Morris, Jeffrey P. Bigham, Robin Brewer, Jonathan Bragg, Anand Kulkarni, Jessie Li, and Saiph Savage. 2017. Subcontracting Microwork. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. ACM, New York, NY, USA, 1867–1876. https://doi.org/10.1145/3025453.3025687

[67] Meredith Ringel Morris, Jaime Teevan, and Katrina Panovich. 2010. What Do People Ask Their Social Networks, and Why?: A Survey Study of Status Message Q&A Behavior. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Atlanta, Georgia, USA) *(CHI '10)*. ACM, New York, NY, USA, 1739–1748. https://doi.org/10.1145/1753326.1753587

[68] Madhumitha Murali and Arzu Çöltekin. 2021. Conducting eye tracking studies online. In *Proceedings of the Workshop on Adaptable Research Methods for Empirical Research with Map Users, Virtual Workshop*, Vol. 6.

[69] Shinichi Nakagawa, Paul CD Johnson, and Holger Schielzeth. 2017. The coefficient of determination R 2 and intra-class correlation coefficient from generalized linear mixed-effects models revisited and expanded. *Journal of the Royal Society Interface* 14, 134 (2017), 20170213.

[70] Sahand Negahban, Sewoong Oh, and Devavrat Shah. 2016. Rank centrality: Ranking from pairwise comparisons. *Operations Research* 65, 1 (2016), 266–287.

[71] Arlene C Neuman, Harry Levitt, Russell Mills, and Teresa Schwander. 1987. An evaluation of three adaptive hearing aid selection strategies. *The Journal of the Acoustical Society of America* 82, 6 (1987), 1967–1976.

[72] Peter O'Donovan, Jānis Lībeks, Aseem Agarwala, and Aaron Hertzmann. 2014. Exploratory font selection using crowdsourced attributes. *ACM Transactions on Graphics (TOG)* 33, 4 (2014), 92.

[73] Gabriele Paolacci and Jesse Chandler. 2014. Inside the Turk: Understanding Mechanical Turk as a participant pool. *Current directions in psychological science* 23, 3 (2014), 184–188.

[74] Alexandra Papoutsaki, James Laskey, and Jeff Huang. 2017. Searchgazer: Webcam eye tracking for remote studies of web search. In *Proceedings of the 2017 Conference on Conference Human Information Interaction and Retrieval (CHIIR '17)*. ACM, New York, NY, USA, 17–26.

[75] Dohyung Park, Joe Neeman, Jin Zhang, Sujay Sanghavi, and Inderjit Dhillon. 2015. Preference completion: Large-scale collaborative ranking from pairwise comparisons. In *International Conference on Machine Learning*. ICML, San Diego, CA, USA, 1907–1916.

[76] Donald G Paterson and Miles A Tinker. 1932. Studies of typographical factors influencing speed of reading. X. Style of type face. *Journal of Applied Psychology* 16, 6 (1932), 605.

[77] Radek Pelánek. 2016. Applications of the Elo rating system in adaptive educational systems. *Computers & Education* 98 (2016), 169–179.

[78] Sandhya Balakrishnan Poodikkalam and Pavithira Loganathan. 2020. Optical character recognition based on local invariant features. *The Imaging Science Journal* 68, 4 (2020), 1–11.

[79] Eustace Christopher Poulton. 1965. Letter differentiation and rate of comprehension in reading. *Journal of Applied Psychology* 49, 5 (1965), 358.

[80] Li Qian, Jinyang Gao, and HV Jagadish. 2015. Learning user preferences by adaptive pairwise comparison. *Proceedings of the VLDB Endowment* 8, 11 (2015), 1322–1333.

[81] Lee Rainie, Kathryn Zickuhr, Kristen Purcell, Mary Madden, and Joanna Brenner. 2012. The Rise of E-Reading. *Pew Internet & American Life Project* (2012), 1–68.

[82] Keith Rayner, Timothy J Slattery, and Nathalie N Bélanger. 2010. Eye movements, the perceptual span, and reading speed. *Psychonomic bulletin & review* 17, 6 (2010), 834–839.

[83] Bryan Reimer, Bruce Mehler, Jonathan Dobres, Joseph F Coughlin, Steve Matteson, David Gould, Nadine Chahine, and Vladimir Levantovsky. 2014. Assessing the impact of typeface design in a text-rich automotive user interface. *Ergonomics* 57, 11 (2014), 1643–1658.

[84] Katharina Reinecke and Krzysztof Z Gajos. 2015. LabintheWild: Conducting large-scale online experiments with uncompensated samples. In *Proceedings of the 18th ACM conference on computer supported cooperative work & social computing*. ACM, New York, NY, USA, 1364–1378.

[85] Joseph F Reisel and Ben Shneiderman. 1986. *Is bigger better? The effects of display size on program reading*. University of Maryland Computer Science, College Park, MD, USA.

[86] Luz Rello and Ricardo Baeza-Yates. 2016. The effect of font type on screen readability by people with dyslexia. *ACM Transactions on Accessible Computing (TACCESS)* 8, 4 (2016), 15.

[87] Luz Rello and Mari-Carmen Marcos. 2012. An eye tracking study on text customization for user performance and preference. In *2012 Eighth Latin American Web Congress*. IEEE, IEEE, Piscataway, NJ, USA, 64–70.

[88] Luz Rello, Martin Pielot, and Mari-Carmen Marcos. 2016. Make it big!: The effect of font size and line spacing on online readability. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, ACM, New York, NY, USA, 3637–3648.

[89] Alexander I Rudnicky and Paul A Kolers. 1984. Size and case of type as stimuli in reading. *Journal of Experimental Psychology: Human Perception and Performance* 10, 2 (1984), 231.

[90] Pragya Paramita Sahu, Vikrant Singh, Indra Kiran, Viswanath Veera, Thanda Abhinav, Ankit Vijay, and Shankar M Venkatesan. 2017. Personalized Hand Writing Recognition Using Continued LSTM Training. In *2017 14th IAPR International Conference on Document Analysis and Recognition (ICDAR)*, Vol. 1. IEEE, IEEE, Piscataway, NJ, USA, 218–223.

[91] Ben D Sawyer, Jonathan Dobres, Nadine Chahine, and Bryan Reimer. 2017. The Cost of Cool: Typographic Style Legibility in Reading at a Glance. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, Vol. 61. SAGE Publications, Los Angeles, CA, USA, 833–837.

[92] Ben D Sawyer, Jonathan Dobres, Nadine Chahine, and Bryan Reimer. 2020. The great typography bake-off: comparing legibility at-a-glance. *Ergonomics* 63, 4 (2020), 391–398.

[93] Ben D Sawyer, Benjamin Wolfe, Jonathan Dobres, Nadine Chahine, Bruce Mehler, and Bryan Reimer. 2020. Glanceable, legible typography over complex backgrounds. *Ergonomics* 63, 7 (2020), 1–20.

[94] Michele Scaltritti, Aliaksei Miniukovich, Paola Venuti, Remo Job, Antonella De Angeli, and Simone Sulpizio. 2019. Investigating Effects of Typographic Variables on Webpage Reading Through Eye Movements. *Scientific reports* 9, 1 (2019), 1–12.

[95] Thomas W Schubert, Carla Murteira, Elizabeth C Collins, and Diniz Lopes. 2013. ScriptingRT: A software library for collecting response latencies in online studies of cognition. *PLoS One* 8, 6 (2013), e67769.

[96] Bonnie Shaver-Troup, Kathy Crowley, and Marjorie Jordan. 2019. Optimizing Reading Performance by Manipulating the Shape, Size, and Spacing of Text to Match the Individual's Visual Processing Capacity. https://readabilitymatters.org/articles/optimizing-reading. (Accessed on 09/20/2019).

[97] Bonnie Shaver-Troup, Kathy Crowley, and Marjorie Jordan. 2019. Optimizing Reading Performance by Manipulating the Shape, Size, and Spacing of Text to Match the Individual's Visual Processing Capacity - Readability Matters. https://readabilitymatters.org/articles/optimizing-reading. (Accessed on 09/20/2019).

[98] Namrata Srivastava, Rajiv Jain, Jennifer Healey, Zoya Bylinskii, and Tilman Dingler. 2021. Mitigating the Effects of Reading Interruptions by Providing Reviews and Previews. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*. ACM, New York, NY, USA, 1–6.

[99] WHATFONTIS COM SRL. 2021. All fonts - What Font Is. https://www.whatfontis.com/all-fonts.html. (Accessed on 01/08/2021).

[100] Yu-Chi Tai, Shun-nan Yang, John Hayes, and James Sheedy. 2012. *Effect of Character Spacing on Text Legibility*. Technical Report. Vision Performance Institute, Pacific University, Oregon, USA. 24 pages.

[101] Myra Thiessen, Sofie Beier, and Hannah Keage. 2020. A Review of the Cognitive Effects of Disfluent Typography on Functional Reading. *The Design Journal* 23, 5 (2020), 797–815.

[102] William Thorn. 2009. International Adult Literacy and Basic Skills Surveys in the OECD Region. 26 (2009). https://doi.org/10.1787/221351213600

[103] Miles Albert Tinker. 1963. *Legibility of print*. Technical Report.

[104] Miles Albert TINKER. 1964. *Legibility of Print.(Second Printing.)*. Ames.

[105] Shaun Wallace, Jonathan Dobres, and Ben D Sawyer. 2021. Considering the Speed and Comprehension Trade-Off in Reading Mediated by Typography. *Journal of Vision* 21, 9 (2021), 2249–2249.

[106] Shaun Wallace, Alexandra Papoutsaki, Neilly H Tan, Hua Guo, and Jeff Huang. 2021. Case Studies on the Motivation and Performance of Contributors Who Verify and Maintain In-Flux Tabular Datasets. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2 (2021), 1–25.

[107] Shaun Wallace, Rick Treitman, Jeff Huang, and Ben D. Sawyer. 2020. Accelerating Adult Readers with Typeface: A Study of Individual Preferences and Effectiveness. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, Extended Abstracts*. ACM, New York, NY, USA, 1–9.

[108] Shaun Wallace, Rick Treitman, Nirmal Kumawat, Kathleen Arpin, Jeff Huang, Ben Sawyer, and Zoya Bylinskii. 2020. Individual Differences in Font Preference & Effectiveness as Applied to Interlude Reading in the Digital Age. *Journal of Vision* 20, 11 (2020), 412–412.

[109] Shaun Wallace, Lucy Van Kleunen, Marianne Aubin-Le Quere, Abraham Peterkin, Yirui Huang, and Jeff Huang. 2017. Drafty: Enlisting Users to be Editors who Maintain Structured Data. In *Proceedings of the Fifth AAAI Conference on Human Computation and Crowdsourcing (HCOMP)*. AAAI, Menlo Park, CA, USA, 187–196.

[110] Jing Wang, Gen Li, and Kai-Lung Hui. 2018. Do Monetary Incentives Create a Spillover Effect on Free Knowledge Contribution? Evidence from a Natural Experiment. *Evidence from a Natural Experiment (June 25, 2018)* (2018), 1–24.

[111] Junxiang Wang, Jianwei Yin, Shuiguang Deng, Ying Li, Calton Pu, Yan Tang, and Zhiling Luo. 2018. Evaluating User Satisfaction with Typography Designs via Mining Touch Interaction Data in Mobile Reading. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. ACM, ACM, New York, NY, USA, 113.

[112] Aleena Watson and Shaun Wallace. 2021. Improving Reading Outcomes Using Digital Reading Rulers for Readers With & Without Dyslexia. *Journal of Vision* 21, 9 (2021), 2650–2650.

[113] Arnold Wilkins, Roanna Cleave, Nicola Grayson, and Louise Wilson. 2009. Typography for children may be inappropriately designed. *Journal of Research in Reading* 32, 4 (2009), 402–412.

[114] Arnold Wilkins, Katie Smith, and Olivier Penacchio. 2020. The influence of typography on algorithms that predict the speed and comfort of reading. *Vision* 4, 1 (2020), 18.

[115] Gary L Williamson. 2008. A text readability continuum for postsecondary readiness. *Journal of Advanced Academics* 19, 4 (2008), 602–632.

[116] Benjamin Wolfe, Jonathan Dobres, Anna Kosovicheva, Ruth Rosenholtz, and Bryan Reimer. 2016. Age-related differences in the legibility of degraded text. *Cognitive Research: Principles and Implications* 1, 1 (2016), 1–13.

[117] Benjamin Wolfe, Ben D Sawyer, and Ruth Rosenholtz. 2020. Toward a theory of visual information acquisition in driving. *Human factors* (2020), 0018720820939693.

[118] Jingwei Xu, Yuan Yao, Hanghang Tong, Xianping Tao, and Jian Lu. 2015. Ice-breaking: mitigating cold-start recommendation problem by rating comparison. In *Twenty-Fourth International Joint Conference on Artificial Intelligence*. IJCAI, California, USA, 3981–3987.

[119] Jinfeng Yi, Rong Jin, Shaili Jain, and Anil Jain. 2013. Inferring users' preferences from crowdsourced pairwise comparisons: A matrix completion approach. In *First AAAI Conference on Human Computation and Crowdsourcing*. AAAI, Palo Alto, CA, USA, 207–215.

[120] Amanda Yung, Pedro Cardoso-Leite, Gillian Dale, Daphne Bavelier, and C Shawn Green. 2015. Methods to test visual attention online. *JoVE (Journal of Visualized Experiments)* 96 (2015), e52470.

[121] Bing Zhang, Ying Li, Ching Y Suen, and Xuemin Zhang. 2011. Discovering legible Chinese typefaces for reading digital documents. In *2011 International Conference on Document Analysis and Recognition*. IEEE, IEEE, Piscataway, NJ, USA, 962–966.

## APPENDIX

## A FONTS USED IN THE MAIN STUDY ON READING EFFECTIVENESS

### A.1 16 Fonts Used in Main Study Sections

**Avenir Next** (AvenirNextLTPro-Regular) Avenir_next.ttc
**Arial** Arial-webfont.woff2
**Avant Garde** ITCAvantGardePro-Bk.otf
**Calibri** calibri.otf
**Franklin Gothic** Franklin_gothic_medium-webfont.woff2
**EB Garamond** Garamond-webfont.woff2
**Helvetica Neue** HelveticaNeueLTStd-Roman.otf
**Lato** Lato-webfont.woff2
**Montserrat** Montserrat-webfont.woff2
**Noto Sans** Noto_sans-webfont.woff2
**Open Sans** Open_sans-webfont.woff2
**Oswald** oswald-webfont.woff2
**Poynter Gothic Text** poynter_gothic_text.otf
**Roboto** Roboto-webfont.woff2
**Times** Timr45w.ttf
**Utopia** utopia.otf

### A.2 4 Fonts Used in the Practice Session

**Comic Sans MS** Comicsansms.ttf
**Georgia** Georgia.ttf
**Raleway** Raleway-webfont.woff2
**Verdana** verdana.ttf

## B FONT NORMALIZATION

The following are the algorithms used to normalize font sizes. When referring to *str* we use the following string of Latin Characters: ABC...Zabc...z012...9.

**Algorithm 1:** How to compute the resultant **width** for a string of text.

```
float width = 0.0;
for (i : str.length()) do
    float characterWidth = font.GetAdvancedWidth(glyphIDs[i]);
    width += characterWidth;
end
Result: resultantWidth = width
```

**Algorithm 2:** How to normalize the target font's **width** with the source font at 16px.

```
float $F_s$ = 16.0;
float deltaForWidth = sourceResultantWidth / targetResultantWidth;
Result: newFontSize = $F_s$ * deltaForWidth
```

**Algorithm 3:** How to compute the resultant **height** for a string of text.

```
float height = 0.0;
float min = +INFINITY;
float max = -INFINITY;
for (i : str.length()) do
    Rect bbox = font.GetTightBoundingBox(glyphIDs[i]);
    if (bbox.yMin < min) then
        min = bbox.yMin
    end
    if (bbox.yMax > max) then
        max = bbox.yMax
    end
end
Result: resultantHeight = max - min
```

**Algorithm 4:** How to normalize the target font's **height** with the source font at 16px.

```
float $F_s$ = 16.0;
float deltaForHeight = sourceResultantHeight / targetResultantHeight;
Result: newFontSize = $F_s$ * deltaForHeight
```

## C EVALUATION METRICS

Elo Ratings have been used for rating chess players [42], in educational settings [77], and to help mitigate cold-start problems in recommender systems [118]. By design, the Elo Rating system aims to minimize the differences between expected and actual outcomes of competitions, or in our case, pairwise comparisons. Elo Rating is an appealing option to determine preference given small sample sizes [47]. This work does not intend to claim that Elo Ratings are better or worse than its alternatives such as TrueSkill [49] and Rank Centrality [70].

For calculating ELO ratings for our fonts, we used the Elo Rating System in [42], started with an initial value set at 1500 per font, and ran the system with a $K$ value of 64, which is higher than usual to account for a small number of pairwise comparisons.

## D PRE-SURVEY QUESTIONS

(1) What is your age? (in years)

(2) What is your gender?

(3) What is/are your native language(s)

(4) What other languages do you speak?

(5) What is your highest attained education level?

(6) Please describe you current occupation:

(7) Do you feel comfortable with reading articles written in English?

(8) How would you rate your speed as a reader?

(9) How would you rate your proficiency as a reader?

(10) Do you read to young children, under the age of 6?

(11) Have you ever been diagnosed with a reading or learning disability (e.g., dyslexia)? If yes, which one and how long ago?

(12) Have you ever been diagnosed with any medical and neurological conditions (macular degeneration, diabetes, ADD, memory disorders, LPD, dyspraxia, etc...) If yes, which one/s and how long ago?

(13) Are you currently under the influence of any drugs, medications, alcohol, or other stimulants (e.g., caffeine, nicotine) that may affect reading/attention? If yes, which?

(14) Do you have normal or corrected vision?

(15) If your vision is corrected, how was it corrected (glasses, lenses, surgery, etc.)?

(16) What device/s do you read on for leisure or personal interest?

(17) What device/s do you read on for work or study?

(18) What do you read for leisure or personal interest?

(19) What do you read for work or study?

(20) How often do you read English written articles for leisure or personal interest?

(21) How often do you read English written articles for work or study?

(22) Which device are you using right now to participate in this study?

(23) Please describe your current surroundings. For example, are you indoors/outside, by a window, under natural or artificial light, is the room light/dark, is the room small/large?

## E POST-SURVEY QUESTIONS

(1) How mentally demanding was the font (toggle) test?

(2) How physically demanding was the font (toggle) test?

(3) How hurried or rushed was the pace of the font (toggle) test?

(4) How successful were you in accomplishing what you were asked to do in the font (toggle) test?

(5) How hard did you have to work to accomplish your level of performance in the font (toggle) test?

(6) How insecure, discouraged, irritated, stressed, and annoyed were you during the font (toggle) test?

(7) How much fun, satisfaction, and enjoyment did you feel during the font (toggle) test?

(8) Can you comment on any strategies you used to complete this study?

(9) What do you think about the font that was recommended to you at the end of the task?

(10) Do you agree with the final font recommendation?

(11) Do you think you would use the recommended font for reading if you had a choice?

(12) How familiar are you with the recommended font?

(13) Do you feel your preferred font would also be your most effective font to read in?

(14) Please describe why you feel this way.

(15) Do you have any other comments about the study, did you find anything confusing?

## F ADDITIONAL PARTICIPANT DEMOGRAPHICS

| **Age Distribution** | **Before (N = 500)** | **After (N = 352)** |
|---|---|---|
| *(ages 18–19)* <20 | 2.0% | 2.3% |
| 20's | 40.8% | 39.8% |
| 30's | 37.6% | 37.8% |
| 40's | 12.7% | 13.5% |
| *(max age 71)* >50 | 6.8% | 6.6% |
| **Education Levels Distribution** | | |
| Less than High School | 0.4% | 0.6% |
| High School/GED | 10.6% | 13.1% |
| Some college | 25.0% | 24.1% |
| Associate's degree (2-years of college) | 11.2% | 11.6% |
| Bachelor's Degree (4-years of college) | 40.4% | 37.8% |
| Master's degree | 10.0% | 9.7% |
| Doctoral degree | 0.8% | 0.9% |
| Professional degree | 1.6% | 2.3% |

Table 1. This table shows the differences in participant age distributions and education levels before and after applying data pre-processing to remove participants from our study's data. The education level distribution of our participants differs from the 18 and over US Population: 9.8% Less than High School, 27.8% High School/GED, 17.5% Some college, 10.1% Associate's degree (2-years of college), 22.1% Bachelor's Degree (4-years of college), 9.5% Master's degree, 1.3% Doctoral degree, and 1.9% Professional degree [23]. A small portion of our participants have less than a high school education.

## G LINEAR MIXED MODEL ANALYSIS

Our linear mixed effect model (LME) for reading comprehension used the same fixed effects as the model for reading speed, except for screen order. This second LME omitted screen order because the multiple-choice reading comprehension questions related to the passage as a whole and not the first or second readings per screen.

Reading comprehension scores could have 3 values (0, 1, or 2 correct answers per passage), with 84% of passages receiving a perfect score. Therefore, we converted the comprehension scores to binary values (1 if completely correct, otherwise 0), and the model was run with a logistic linking function.

All our LMEs were checked for multicollinearity by calculating the variance inflation factors (VIF) of all fixed effect predictors. All VIFs were in the range of 1-3, indicating negligible multicollinearity [44].

Given our model's significant order effects, we performed further checks to verify that passage order and font order were sufficiently randomized across all participants. The mixed effect models that predicted presentation order from participant ID as a random effect and font (or passage) as a fixed effect showed that both were sufficiently randomized. This shows the ordering was not dependent on font or passage ($X^2_{14} = 17.8$, $p = 0.215$ and $X^2_9 = 7.45$, $p = 0.590$, respectively).

In light of the dramatically different reading speeds observed for first and second screens, two new models were run for first and second screen data separately. These models are the same as the one described for WPM outcomes above, except for the removal of the screen order predictor in each. In the first-screen model, WPM was significantly affected by passage order (1.02 WPM/passage; $R^2_\beta = 0.001$; $p = 0.009$), reading device ($p = 0.010$; tablet = 213 WPM, phone = 223 WPM, laptop = 249 WPM, desktop = 267 WPM), participant age (-1.2 WPM/year; $R^2_\beta = 0.018$; $p = 0.001$), font familiarity ($R^2_\beta = 0.002$; $p = 0.003$), and topic familiarity ($R^2_\beta = 0.003$; $p = 0.009$). In addition, there was a borderline significant effect of font ($p = 0.057$), but no significant difference between fiction and non-fiction passages ($p = 0.963$).

In the second-screen model, reading speed was significantly affected by participant age (-1.87 WPM/year; $R^2_\beta = 0.025$; $p < 0.001$), passage order (2.4 WPM/passage; $R^2_\beta = 0.003$; $p < 0.001$), whether the passage was fiction (fiction passages were read 26 WPM faster than non-fiction; $R^2_\beta = 0.013$, $p < 0.001$), and topic familiarity ($R^2_\beta = 0.002$; $p = 0.007$). No other predictors were significant or near significance.

Lastly, given the differential effect of font between the first-screen and second-screen models, the full dataset model was re-run with font and screen order included in an interaction term. The interaction was non-significant ($p = 0.323$), as was also the case among the cohort of older participants ($p = 0.832$), suggesting that font did not exert differential effects on reading speed between the two screens.

## H MODEL RESULTS

This section provides detailed reporting for all linear mixed effects models reported in the present study, including the first-screen and second-screen models described in the previous section.

Conditional and marginal model $R^2$ values are computed for the overall models following methods described by Nakagawa et al. [69]. The marginal $R^2$ ($R^2_m$) estimates the variance explained by the model's fixed effects, while the conditional $R^2$ ($R^2_c$) estimates the variance explained by fixed and random effects together.

Effect size measures for significant model coefficients are calculated as $R^2_\beta$ following Edwards et al. [41], as described in the main reporting of results. We also report standardized betas alongside these results as an alternative metric of effect size, though we caution that the interpretation of standardized betas can be confounded if different predictors have markedly different underlying variances.

Coefficient tests of significance are presented as Analysis of Deviance tables using Type II Wald $X^2$ tests. This test was necessitated by the comprehension score tests' use of general linear mixed effect models with a binomial linking function. The same statistical testing framework is used across all models for consistency.

Finally, intra-class correlations (ICCs) are reported to further describe the impact of each model's random effects on its outcome measure. We also include the results of checks for multicollinearity for completeness.

### H.1 WPM: All Participants

The model specifies participant ID and passage read as crossed *random effects* with intercepts per level of participant and passage, and constant slopes for both. The model specifies the following as *fixed effects*: participant age, reading device, passage order, screen order, font, non-fiction status, topic familiarity, topic interest, and font familiarity. Screen order refers to participants reading each passage split across two consecutive screens.

The model has a $R^2_m$ of 0.081 and a $R^2_c$ of 0.653, consistent with the idea that the model's random effects, here representing inter-participant and inter-passage differences, account for much of the variance in reading speed. The model has adjusted ICC of 0.622 and conditional ICC (accounting for fixed effects) of 0.572.

| Fixed Effect | $X^2$ | k | p |
|---|---|---|---|
| Participant Age (Years) | 12.72 | 1 | $< 0.001$ * |
| Reading Device | 7.49 | 3 | 0.058 |
| Font | 19.38 | 15 | 0.197 |
| Passage Order | 30.47 | 1 | $< 0.001$ * |
| Screen Number | 699.79 | 1 | $< 0.001$ * |
| Non-Fiction | 6.93 | 1 | 0.008 * |
| Passage Familiarity | 11.81 | 1 | $< 0.001$ * |
| Passage Interest | 0.21 | 1 | 0.645 |
| Font Familiarity | 2.96 | 1 | 0.086 |

Table 2. Analysis of Deviance Table (Type II Wald $X^2$ tests) showing the effect of model predictors on WPM across all participants.

| Effect | $R^2_\beta$ | Standardized $\beta$ |
|---|---|---|
| Screen Number | 0.0432 | 0.2125 |
| Participant Age (Years) | 0.0191 | -0.1394 |
| Non-Fiction | 0.0040 | 0.0660 |
| Passage Order | 0.0021 | 0.0460 |
| Passage Familiarity | 0.0019 | 0.0456 |

Table 3. Effect sizes measures calculated as $R^2_\beta$ and standardized $\beta$ for all significant model coefficients

| Term | VIF | SE Factor |
|---|---|---|
| Participant Age (Years) | 1.03 | 1.01 |
| Reading Device | 1.03 | 1.01 |
| Font | 1.30 | 1.14 |
| Passage Order | 1.01 | 1.00 |
| Screen Number | 1.00 | 1.00 |
| Non-Fiction | 1.02 | 1.01 |
| Passage Familiarity | 1.10 | 1.05 |
| Passage Interest | 1.08 | 1.04 |
| Font Familiarity | 1.28 | 1.13 |

Table 4. Variance inflation factors (VIFs) calculated to check for multicollinearity. A VIF of $> 5$ is an indication of high multicollinearity

.

### H.2 WPM: Older Participants

The model specification is identical to the one described in H.1, but the analysis considers only participants with a self-reported age of 35 years or greater.

The model has a $R^2_m$ of 0.128 and a $R^2_c$ of 0.705, consistent with the idea that the model's random effects, here representing inter-participant and inter-passage differences, account for much of the variance in reading speed. The model has adjusted ICC of 0.661 and conditional ICC (accounting for fixed effects) of 0.577.

| Fixed Effect | $X^2$ | k | p |
|---|---|---|---|
| Participant Age (Years) | 9.47 | 1 | 0.002 * |
| Reading Device | 7.75 | 3 | 0.052 |
| Font | 30.61 | 15 | 0.010 * |
| Passage Order | 13.20 | 1 | $< 0.001$ * |
| Screen Number | 247.98 | 1 | $< 0.001$ * |
| Non-Fiction | 9.40 | 1 | 0.002 * |
| Passage Familiarity | 8.48 | 1 | 0.004 * |
| Passage Interest | 0.83 | 1 | 0.362 |
| Font Familiarity | 1.10 | 1 | 0.294 |

Table 5. Analysis of Deviance Table (Type II Wald $X^2$ tests) showing the effect of model predictors on WPM across older participants.

| Effect | $R^2_\beta$ | Standardized $\beta$ |
|---|---|---|
| Screen Number | 0.0396 | 0.2025 |
| Participant Age (Years) | 0.0386 | -0.2041 |
| Non-Fiction | 0.0064 | 0.0867 |
| Passage Familiarity | 0.0026 | 0.0550 |
| Passage Order | 0.0023 | 0.0481 |
| (Font) Avantgarde | 0.0016 | -0.0426 |
| (Font) Oswald | 0.0013 | -0.0381 |
| (Font) Utopia | 0.0008 | -0.0311 |
| (Font) Franklin Gothic | 0.0004 | 0.0234 |
| (Font) Calibri | 0.0003 | 0.0232 |
| (Font) Open Sans | 0.0002 | -0.0144 |
| (Font) Helvetica | 0.0001 | -0.0105 |
| (Font) Avenir Next | 0.0001 | -0.0098 |
| (Font) Montserrat | 0.0001 | 0.0097 |
| (Font) Times | 0.0001 | 0.0124 |
| (Font) Lato | 0.0000 | -0.0073 |
| (Font) Poynter Gothic Text | 0.0000 | 0.0053 |
| (Font) Garamond | 0.0000 | -0.0010 |
| (Font) Noto Sans | 0.0000 | 0.0013 |
| (Font) Roboto | 0.0000 | 0.0004 |

Table 6. Effect sizes measures calculated as $R^2_\beta$ and standardized $\beta$ for all significant model coefficients

### H.3 Comprehension: All Participants

The model specification is identical to the one described in section H.1, other than the following differences. Screen Number is removed as a predictor because comprehension questions were associated with whole passages and not their individual screens. The comprehension score outcome is binarized as either perfect comprehension (84% of comprehension tests) or not. Lastly, the model was run as a general linear mixed effects model using a logistic linking function.

| Term | VIF | SE Factor |
|---|---|---|
| Participant Age (Years) | 1.03 | 1.02 |
| Reading Device | 1.03 | 1.02 |
| Font | 1.31 | 1.15 |
| Passage Order | 1.02 | 1.01 |
| Screen Number | 1.00 | 1.00 |
| Non-Fiction | 1.08 | 1.04 |
| Passage Familiarity | 1.19 | 1.09 |
| Passage Interest | 1.11 | 1.06 |
| Font Familiarity | 1.25 | 1.12 |

Table 7. Variance inflation factors (VIFs) calculated to check for multicollinearity. A VIF of $>5$ is an indication of high multicollinearity

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The model has a $R_m^2$ of 0.098 and a $R_c^2$ of 0.215, suggesting that the model's random effects (participant and passage) account for relatively little of the variation in comprehension scores compared to WPM. The model has adjusted ICC of 0.129 and conditional ICC (accounting for fixed effects) of 0.116.

| Fixed Effect | $X^2$ | k | p |
|---|---|---|---|
| Passage ID | 1.03 | 1 | 0.310 |
| Reading Device | 2.88 | 3 | 0.411 |
| Font | 15.57 | 15 | 0.411 |
| Participant Age (Years) | 1.39 | 1 | 0.238 |
| Passage Order | 0.49 | 1 | 0.485 |
| Font Familiarity | 1.70 | 1 | 0.192 |
| Passage Familiarity | 0.49 | 1 | 0.482 |
| Passage Interest | 47.95 | 1 | $< 0.001$ * |
| Non-Fiction | 6.13 | 1 | 0.013 * |

Table 8. Analysis of Deviance Table (Type II Wald $X^2$ tests) showing the effect of model predictors on comprehension scores across all participants.

| Effect | $R_\beta^2$ | Standardized $\beta$ |
|---|---|---|
| Passage Interest | 0.0188 | 1.1456 |
| Non-Fiction | 0.0176 | 1.1707 |

Table 9. Effect sizes measures calculated as $R_\beta^2$ and standardized $\beta$ for all significant model coefficients

| Term | VIF | SE Factor |
|---|---|---|
| Passage ID | 2.72 | 1.65 |
| Reading Device | 1.06 | 1.03 |
| Font | 1.27 | 1.13 |
| Participant Age (Years) | 1.04 | 1.02 |
| Passage Order | 1.01 | 1.00 |
| Font Familiarity | 1.22 | 1.10 |
| Passage Familiarity | 1.16 | 1.08 |
| Passage Interest | 1.15 | 1.07 |
| Non-Fiction | 2.69 | 1.64 |

Table 10. Variance inflation factors (VIFs) calculated to check for multicollinearity. A VIF of $>5$ is an indication of high multicollinearity

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### H.4 Comprehension: Older Participants

The model is specified exactly as described in H.3, but the analysis considers only participants with a self-reported age of 35 years or greater.

The model has a $R_m^2$ of 0.653 and a $R_c^2$ of 0.693, suggesting that the model's random effects (participant and passage) account for more of the variation in comprehension scores. The model has adjusted ICC of 0.116 and conditional ICC (accounting for fixed effects) of 0.040.

| Fixed Effect | $X^2$ | k | p |
|---|---|---|---|
| Reading Device | 11.18 | 3 | 0.011 * |
| Font | 12.11 | 15 | 0.671 |
| Participant Age (Years) | 3.96 | 1 | 0.047 * |
| Passage Order | 1.79 | 1 | 0.181 |
| Font Familiarity | 0.00 | 1 | 0.978 |
| Passage Familiarity | 0.17 | 1 | 0.676 |
| Passage Interest | 18.87 | 1 | $< 0.001$ * |
| Non-Fiction | 7.75 | 1 | 0.005 * |

Table 11. Analysis of Deviance Table (Type II Wald $X^2$ tests) showing the effect of model predictors on comprehension scores across older participants.

| Effect | $R^2_\beta$ | Standardized $\beta$ |
|---|---:|---:|
| Non-Fiction | 0.0279 | 1.9758 |
| Passage Interest | 0.0180 | 1.4524 |
| (Device) Phone | 0.0048 | -0.7801 |
| (Device) Laptop | 0.0028 | -0.6241 |
| Participant Age (Years) | 0.0017 | -0.4710 |
| (Device) Tablet | 0.0000 | -0.0657 |

Table 12. Effect sizes measures calculated as $R^2_\beta$ and standardized $\beta$ for all significant model coefficients

| Term | VIF | SE Factor |
|---|---:|---:|
| Reading Device | 1.20 | 1.09 |
| Font | 1.40 | 1.18 |
| Participant Age (Years) | 1.09 | 1.04 |
| Passage Order | 1.02 | 1.01 |
| Font Familiarity | 1.18 | 1.09 |
| Passage Familiarity | 1.24 | 1.11 |
| Passage Interest | 1.21 | 1.10 |
| Non-Fiction | 1.04 | 1.02 |

Table 13. Variance inflation factors (VIFs) calculated to check for multicollinearity. A VIF of $>5$ is an indication of high multicollinearity

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### H.5 WPM: First Screens

The model specification is identical to the one described in section H.1, but the analysis considers only WPM measures collected from each passage's first screen. Therefore screen order is dropped as a predictor.

The model has a $R^2_m$ of 0.044 and a $R^2_c$ of 0.651, consistent with the idea that the model's random effects, here representing inter-participant and inter-passage differences, account for much of the variance in reading speed. The model has adjusted ICC of 0.635 and conditional ICC (accounting for fixed effects) of 0.607.

| Fixed Effect | $X^2$ | k | p |
|---|---:|---:|---|
| Participant Age (Years) | 10.41 | 1 | 0.001 * |
| Reading Device | 11.36 | 3 | 0.010 * |
| Font | 24.51 | 15 | 0.057 |
| Passage Order | 6.76 | 1 | 0.009 * |
| Non-Fiction | 0.00 | 1 | 0.963 |
| Passage Familiarity | 6.77 | 1 | 0.009 * |
| Passage Interest | 0.00 | 1 | 0.955 |
| Font Familiarity | 8.59 | 1 | 0.003 * |

Table 14. Analysis of Deviance Table (Type II Wald $X^2$ tests) showing the effect of model predictors on WPM on the first screen only, across all participants.

| Effect | $R^2_\beta$ | Standardized $\beta$ |
|---|---|---|
| Participant Age (Years) | 0.0184 | -0.1392 |
| (Device) Laptop | 0.0126 | -0.1186 |
| (Device) Tablet | 0.0080 | -0.0919 |
| (Device) Phone | 0.0057 | -0.0775 |
| Passage Familiarity | 0.0026 | 0.0519 |
| Font Familiarity | 0.0017 | 0.0420 |
| Passage Order | 0.0009 | 0.0296 |

Table 15. Effect sizes measures calculated as $R^2_\beta$ and standardized $\beta$ for all significant model coefficients

| Term | VIF | SE Factor |
|---|---|---|
| Participant Age (Years) | 1.03 | 1.01 |
| Reading Device | 1.03 | 1.01 |
| Font | 1.30 | 1.14 |
| Passage Order | 1.01 | 1.00 |
| Non-Fiction | 1.01 | 1.00 |
| Passage Familiarity | 1.08 | 1.04 |
| Passage Interest | 1.07 | 1.04 |
| Font Familiarity | 1.28 | 1.13 |

Table 16. Variance inflation factors (VIFs) calculated to check for multicollinearity. A VIF of $>5$ is an indication of high multicollinearity

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### H.6 WPM: Second Screens

The model specification is identical to the one described in section H.5, but considers only WPM measures collected from each passage's second screen.

The model has a $R^2_m$ of 0.051 and a $R^2_c$ of 0.686, consistent with the idea that the model's random effects, here representing inter-participant and inter-passage differences, account for much of the variance in reading speed. The model has adjusted ICC of 0.669 and conditional ICC (accounting for fixed effects) of 0.635.

| Fixed Effect | $X^2$ | k | p |
|---|---|---|---|
| Participant Age (Years) | 13.98 | 1 | $< 0.001$ * |
| Reading Device | 3.74 | 3 | 0.291 |
| Font | 16.01 | 15 | 0.381 |
| Passage Order | 25.80 | 1 | $< 0.001$ * |
| Non-Fiction | 14.32 | 1 | $< 0.001$ * |
| Passage Familiarity | 7.16 | 1 | 0.007 * |
| Passage Interest | 1.19 | 1 | 0.275 |
| Font Familiarity | 0.00 | 1 | 0.993 |

Table 17. Analysis of Deviance Table (Type II Wald $X^2$ tests) showing the effect of model predictors on WPM on the second screen only, across all participants.

| Effect | $R^2_\beta$ | Standardized $\beta$ |
|---|---|---|
| Participant Age (Years) | 0.0254 | -0.1646 |
| Non-Fiction | 0.0132 | 0.1229 |
| Passage Order | 0.0033 | 0.0584 |
| Passage Familiarity | 0.0017 | 0.0438 |

Table 18. Effect sizes measures calculated as $R^2_\beta$ and standardized $\beta$ for all significant model coefficients

| Term | VIF | SE Factor |
|---|---|---|
| Participant Age (Years) | 1.03 | 1.01 |
| Reading Device | 1.03 | 1.01 |
| Font | 1.30 | 1.14 |
| Passage Order | 1.01 | 1.00 |
| Non-Fiction | 1.03 | 1.01 |
| Passage Familiarity | 1.10 | 1.05 |
| Passage Interest | 1.08 | 1.04 |
| Font Familiarity | 1.28 | 1.13 |

Table 19. Variance inflation factors (VIFs) calculated to check for multicollinearity. A VIF of $>5$ is an indication of high multicollinearity

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## I ADDITIONAL FINDINGS ON FONT PREFERENCE

In this section we present a few additional findings from the toggle-based font preference test.

*Can Dwell Time predict preference?* We found that participants viewed the winning font 31% longer, 3.5 seconds than the losing font. We conducted a Paired two sample t-test to show dwell Time and font preference ($t(15102) = 46.6$, $p < 0.01$) have a predictive relationship in our scenario. The fonts with the highest Elo Ratings, Noto Sans and Helvetica, also had the highest average dwell time per pairwise comparison. Qualitative evidence from the post-survey indicates participants found it more difficult to pick between their most preferred fonts, but overall were satisfied with the final font recommendation and agreed with it 88% of the time. This result aligns with previous findings aligning fixation, measured via eye trackers, and satisfaction [17, 18].

*Does familiarity drive font preference?* This covers additional discussion around our results for font familiarity and preference. Arial, Times, Calibri, and Helvetica were rated as most familiar, on average, by participants on the post-survey (Fig. §10, 'Font Familiarity'). In contrast, Oswald, Lato, Franklin Gothic, and Montserrat were rated least familiar. From the pre-survey responses, we can confirm that if people mostly read novels and news for leisure, then the most familiar rated fonts make sense. However, familiarity was not predictive of font preference. Participants were familiar with their recommended font only 52% of the time. After controlling for font-size in this study, Pearson's Correlation shows little effect between font familiarity and Elo Rating per font per participant ($r = 0.18$, $p < 0.05$). Similar to the preliminary study, the most preferred font, Noto Sans, was also among the least familiar fonts to participants.

## J FONT MATCHUPS FROM THE READING SPEED TEST

| Font | Speed Measurements | Speed Rank* |
|---|---:|---:|
| arial | 467 | 44% |
| calibri | 459 | 57% |
| roboto | 225 | 50% |
| lato | 96 | 50% |
| poynter gothic text | 92 | 54% |
| avenir next | 90 | 48% |
| montserrat | 87 | 49% |
| franklin gothic | 86 | 63% |
| utopia | 85 | 44% |
| oswald | 83 | 58% |
| garamond | 82 | 50% |
| helvetica | 81 | 53% |
| avantgarde | 79 | 29% |
| open sans | 68 | 46% |

Table 20. This table shows the number of reading speed measurements used in our final data analysis per font from our 352 crowdsourced participants in the main study. This excludes Times and Noto Sans, which every participant read. *This version of the Speed Rank metric does not include comparing reading speed measurements from a font with Times or Noto Sans.

| Font 1 | Font 2 | Times Read | How often was Font 1 faster? |
|---|---|---:|---:|
| arial | calibri | 218 | 40% |
| calibri | roboto | 107 | 54% |
| arial | roboto | 106 | 42% |
| arial | avenir next | 25 | 56% |
| avenir next | calibri | 24 | 46% |
| arial | helvetica | 23 | 39% |
| calibri | helvetica | 23 | 48% |
| arial | eb garamond | 20 | 50% |
| calibri | eb garamond | 20 | 60% |
| arial | open sans | 15 | 40% |
| poynter gothic text | utopia | 15 | 53% |
| arial | oswald | 14 | 57% |
| calibri | open sans | 14 | 57% |
| lato | montserrat | 13 | 54% |
| franklin gothic | poynter gothic text | 13 | 54% |
| arial | utopia | 12 | 58% |
| lato | poynter gothic text | 12 | 58% |
| lato | oswald | 12 | 25% |
| calibri | utopia | 11 | 64% |
| calibri | oswald | 11 | 64% |
| avantgarde | montserrat | 11 | 36% |
| avantgarde | oswald | 11 | 0% |
| calibri | montserrat | 10 | 60% |
| arial | montserrat | 9 | 33% |
| arial | franklin gothic | 9 | 44% |
| montserrat | poynter gothic text | 9 | 56% |
| avantgarde | poynter gothic text | 9 | 44% |
| avantgarde | franklin gothic | 9 | 11% |
| franklin gothic | lato | 9 | 33% |
| franklin gothic | utopia | 9 | 89% |
| arial | avantgarde | 8 | 75% |
| arial | lato | 7 | 86% |
| montserrat | oswald | 7 | 29% |
| helvetica | lato | 7 | 43% |
| helvetica | poynter gothic text | 7 | 43% |
| eb garamond | poynter gothic text | 7 | 43% |
| open sans | poynter gothic text | 7 | 29% |
| avantgarde | calibri | 6 | 50% |
| calibri | franklin gothic | 6 | 50% |
| calibri | lato | 6 | 33% |
| lato | utopia | 6 | 33% |

Table 21. **Reading Speed Matchups Part 1.** This table features the number of times a participant read using Font 1 and Font 2 during the main study featuring 352 paid crowdworkers. This table includes the more frequent pairings. Every participant read in Times and Noto Sans. Excluding these two fonts, we observed 87 font pairings. However, different pairs had different sampling rates: Participants compared 38 pairs less than five times, whereas 3 of the pairs (Arial vs. Calibri, Arial vs. Roboto, and Calibri vs. Roboto) were compared over 100 times each.

| Font 1 | Font 2 | Times Read | How often was Font 1 was faster? |
|---|---|---:|---:|
| avantgarde | utopia | 6 | 50% |
| franklin gothic | montserrat | 6 | 67% |
| eb garamond | oswald | 6 | 67% |
| montserrat | open sans | 6 | 50% |
| lato | open sans | 6 | 67% |
| montserrat | utopia | 6 | 67% |
| avantgarde | lato | 5 | 40% |
| franklin gothic | oswald | 5 | 80% |
| avenir next | utopia | 5 | 60% |
| helvetica | oswald | 5 | 20% |
| franklin gothic | eb garamond | 5 | 40% |
| avenir next | poynter gothic text | 5 | 0% |
| avenir next | lato | 5 | 40% |
| eb garamond | lato | 5 | 80% |
| avenir next | montserrat | 5 | 80% |
| avenir next | franklin gothic | 5 | 20% |
| franklin gothic | open sans | 5 | 80% |
| oswald | poynter gothic text | 4 | 75% |
| avantgarde | avenir next | 4 | 25% |
| helvetica | utopia | 4 | 50% |
| avantgarde | open sans | 4 | 50% |
| eb garamond | utopia | 4 | 50% |
| avenir next | open sans | 4 | 75% |
| calibri | poynter gothic text | 3 | 33% |
| lato | roboto | 3 | 100% |
| avantgarde | eb garamond | 3 | 0% |
| oswald | utopia | 3 | 0% |
| avantgarde | helvetica | 3 | 33% |
| eb garamond | montserrat | 3 | 33% |
| franklin gothic | roboto | 3 | 33% |
| eb garamond | helvetica | 3 | 33% |
| avenir next | eb garamond | 3 | 67% |
| roboto | utopia | 2 | 0% |
| avenir next | oswald | 2 | 100% |
| open sans | oswald | 2 | 0% |
| helvetica | montserrat | 2 | 50% |
| franklin gothic | helvetica | 2 | 50% |
| open sans | utopia | 2 | 100% |
| avenir next | helvetica | 2 | 0% |
| eb garamond | open sans | 2 | 0% |
| arial | poynter gothic text | 1 | 0% |
| oswald | roboto | 1 | 100% |
| open sans | roboto | 1 | 100% |
| avenir next | roboto | 1 | 100% |
| eb garamond | roboto | 1 | 100% |

Table 22. **Reading Speed Matchups Part 2.** This table features the number of times a participant read using Font 1 and Font 2 during the main study featuring 352 paid crowdworkers. This table is a continuation of Table §21, and includes the matchups that occurred less frequently.

## K COMPARING FONT USAGE AND RESULTS WITH PRIOR RESEARCH

| | | | Font | Size | Age | Preference | Familiarity | Serifs | Italics | Font | Size |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Paper** | **Year** | **Language** | *Speed* | *Speed* | *Speed* | *Speed* | *Speed* | *Speed* | *Speed* | *Preference* | *Preference* |
| Wallace | Present | English | yes* | | yes | no | no | | | yes | yes |
| Wallace | 2020 | English | no | | | no | | | | yes | |
| Chatrangsan | 2019 | English/Thai | yes | yes | | | | | | | yes |
| Wang | 2018 | Chinese | | | | yes | | | yes | | |
| Rello | 2016 | English | | yes | | | | | | | yes |
| Rello | 2016 | Spanish | yes | | | | | yes | | yes | |
| Beier | 2013 | English | | | | | yes | | | | |
| Bhatia | 2011 | English | | no | | | | | | no | no |
| Banerjee | 2011 | English | yes | yes | | | | | | yes | yes |
| Beymer | 2008 | English | no | no | yes | | | no | | | |
| Darroch | 2005 | English | | no | no | | | | | | yes |
| Bernard | 2003 | English | no** | yes | | | | | | | yes |
| Boyarski | 1998 | English | no | | | | | no | no | | |

Fig. 16. This figure summarizes the findings from related readability studies. It highlights if a readability study found a relationship between Font and Reading Speed or Font Size and Reading Speed. This figure shows that readability research has not reached a consensus over the past two decades on these various relationships. * Our work found that fonts need to be individualized per participant to maximize possible reading speed gains. ** The authors found a relationship between font choice and reading time. They did not find any results when adjusting for reading accuracy, a metric they used that combines reading speed and comprehension.

| | Present | 2020 | 2019 | 2018 | 2016 | 2016 | 2013 | 2011 | 2011 | 2008 | 2005 | 2003 | 1998 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Wallace | Wallace | Chatrangsan | Wang | Rello | Rello | Beier | Bhatia | Banerjee | Beymer | Darroch | Bernard | Boyarski |
| Total Fonts | 16 | 16 | 4 | 1* | 1 | 12 | 6 | 1* | 6 | 2 | 1 | 2 | 4 |
| Arial | ✓ | ✓ | ✓ | | ✓ | ✓ | | | ✓ | | | ✓ | |
| Avant Garde | ✓ | ✓ | | | | | | | | | | | |
| Avenir Next | ✓ | ✓ | | | | | | | | | | | |
| Calibri | ✓ | ✓ | | | | | | | | | | | |
| Courier | | | | | | ✓ | | | ✓ | | | | |
| EB Garamond | ✓ | ✓ | | | | ✓ | | | | | | | |
| Franklin Gothic | ✓ | ✓ | | | | | | | | | | | |
| Georgia | | | | | | | | | ✓ | ✓ | | | ✓ |
| Helvetica | ✓ | ✓ | | | | ✓ | ✓ | | | ✓ | ✓ | | |
| Lato | ✓ | ✓ | | | | | | | | | | | |
| Montserrat | ✓ | ✓ | | | | | | | | | | | |
| Noto Sans | ✓ | ✓ | | | | | | | | | | | |
| Open Sans | ✓ | ✓ | | | | | | | | | | | |
| Oswald | ✓ | ✓ | | | | | | | | | | | |
| Poynter Gothic | ✓ | ✓ | | | | | | | | | | | |
| Roboto | ✓ | ✓ | | | | | | | | | | | |
| Times | ✓ | ✓ | ✓ | | | ✓ | ✓ | | ✓ | | | ✓ | ✓ |
| Utopia | ✓ | ✓ | | | | | | | | | | | |
| Verdana | | | | | | ✓ | | | ✓ | | | | ✓ |
| Did not Disclose | | | | N/A | | | | N/A | | | | | |

Fig. 17. This table features a summary of fonts used by our study and past readability studies. Some studies featuring 1 font, like Rello et al. [88], only feature a single font because the study focused on font size and line spacing. * Courier (or, Courier New), Georgia, and Verdana are fonts often featured in past studies but are not a part of our main study. ** These two studies only used 1 font each, and to the best of our knowledge did not disclose the fonts they used.