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 words-per-minute (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 article.

CCS Concepts: • **Human-centered computing** → **Human computer interaction (HCI)**; *User studies*; *Empirical studies in HCI*; *Web-based interaction*; *Visualization design and evaluation methods*;

Additional Key Words and Phrases: Reading, typography, text, individuation, crowdsourcing

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 e-mail, 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 [96]. 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 article, 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 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. Furthermore, to help future researchers, we open-source our web applications and reading materials with this article.[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 (Figure 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 article [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.

2.1 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 is e-reader [81]. In this reading mode, evidence for the impact of font choice

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[1]16px is the default font size in Firefox and Chrome.
[2]Available at https://github.com/virtual-readability-lab/tochi-paper-materials-towards-individuated-reading.
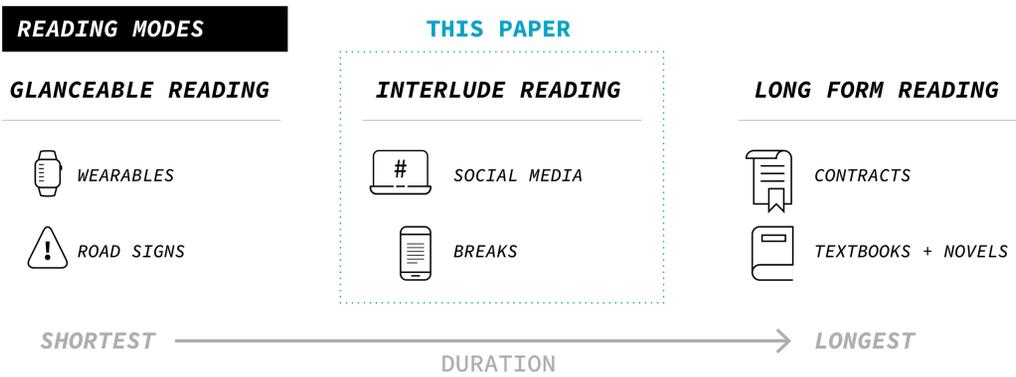
Fig. 1. Reading modes can be viewed on a duration continuum, ranging from the well studied domains of Glanceable Reading (few words, few seconds) to Long Form reading (long documents, minutes to hours). Interlude Reading, as introduced in this article, falls between these two reading modes. We define 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.

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

Paper	Year	N	Fonts	Sizes	Age Range	Speed	Comp.	Pref.	Fam.	Acc.	Eye mov.
					Independent Variables	Dependent Variables					
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).

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 (Section 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.

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 Figure 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 four 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 62–83 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, and 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 handheld 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 eye tracking 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 (average 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, and 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 United Kingdom to read in Thai and English, respectively. They compared three font sizes (14, 16, and 18 point) in four fonts across both groups—UK: Times New Roman and Arial; Thailand: serif (TH sarabun) and sans-serif typeface (Kanit). Participants picked their most preferred fonts among six 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 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 at capturing popular fonts across various media and periods ranging from print to digital. The 16 fonts (Figure 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 Section 7.3). Even within this group, Helvetica is a common

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[3]Found by analyzing a corpus of 2,302 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.

	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 four 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 Section A for the filenames used for each font.

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, 97] 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

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[4]https://fonts.google.com/analytics. [Accessed August 2019]

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 three serif and 13 sans-serif fonts across different classifications. We include various fonts classified as sans-serif: three Neo-Grotesque, three Geometric, three Humanist, three Gothic, and one Modern; our serif fonts include: two Old Style and one 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, five 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 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?" (Figure 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

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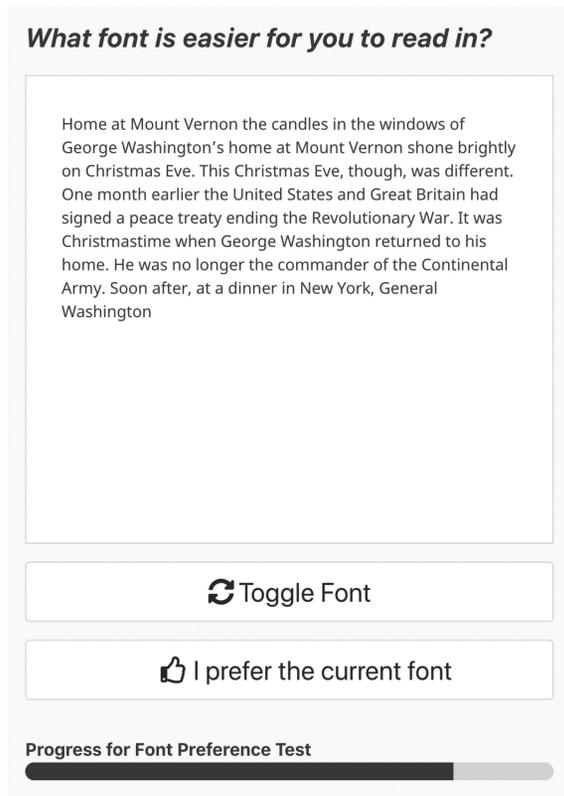
Fig. 4. Font preference toggle test: A participant toggles between pairs of fonts to decide which one is easier to read in. The interface is a fixed width of 420px regardless of the device. All text is rendered with a line spacing of 1.5. Custom JavaScript is used to ensure participants cannot modify 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.

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 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; and (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]. Furthermore, 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 (Section 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

REFERENCE FONT
TIMES 16px   h Rewashington x

w

Reference
underlay   Rewashington

Oswald Font
Fixed Pixel Size   Ⓜ Rewashington   ADJUSTED SIZE
16px

MATCH X   Ⓧ Rewashington   12.5px

MATCH H   Ⓗ Rewashington   13.3px

MATCH W   Ⓦ Rewashington   18px

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.

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** (Figure 5). The paragraphs below describe each normalization method in detail.

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

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 Δ as (*sourceXHeight* / *targetXHeight*). Finally, we compute the target font's new font size $NewF_s$, so it matches the reference font in x-height: $NewF_s = F_s \times \Delta$.

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 article.

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.

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 (Figure 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
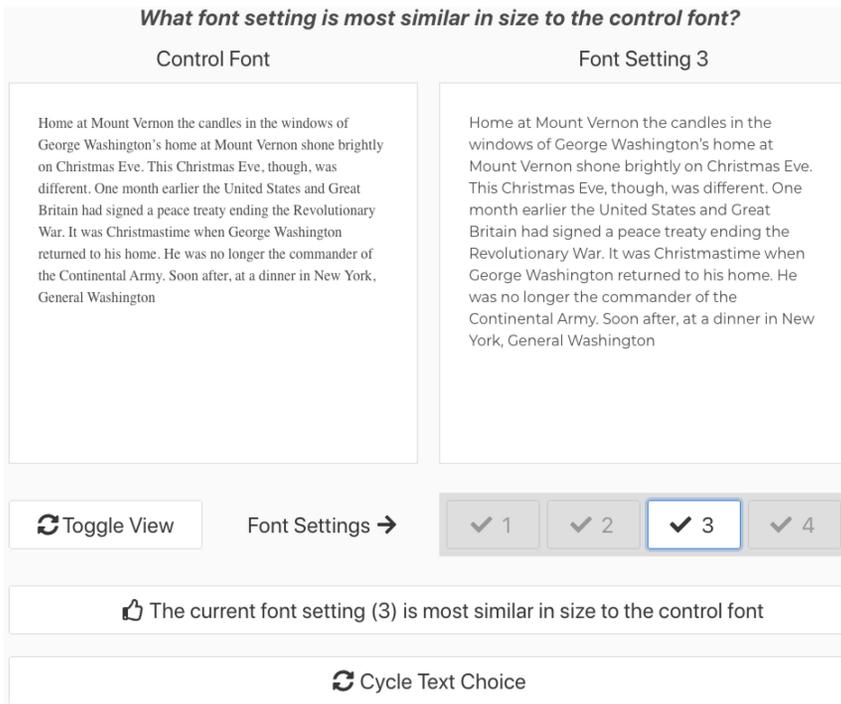
Fig. 6. To normalize font size, crowdworkers see a control (reference) font in one panel and a target font in the other. They can toggle between four different target font settings, which corresponds to adjusting the font size to match the reference in x-height, width, height, and original size (16px). 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.

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 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 (Figure 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 (Figure 6). Previous articles 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

TIMES 16px	ADJUSTMENT	Oswald	Montserrat	EB Garamond	Avenir Next
Rewashington	ⓜ Fixed Pixel Size ⓜ	Rewashington	Rewashington	Rewashington	Rewashington
Rewashington	ⓧ MATCH X	Rewashington	ⓧRewashington	Rewashington	Rewashington
Rewashington	ⓗ MATCH H	Rewashington	Rewashington	Rewashington	ⓗRewashington
Rewashington	ⓦ MATCH W	Rewashington	Rewashington	ⓦRewashington	Rewashington

OPTIMAL SELECTED ADJUSTMENT	ⓜRewashington	ⓧRewashington	ⓦRewashington	ⓗRewashington
ADJUSTED SIZE	16px	13.7px	16.4px	15px

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.

wisdom and show that the preferred way to normalize a font actually depends on the font itself. Figure 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 (Figure 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 Figure 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.

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 article. 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.

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, and 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.

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

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[7]https://www.gutenberg.org.

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 article for future reading studies.[10] We selected nine non-fiction and three 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 two 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 (Section 5.1.3). We selected two 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, and native language), reading experience (frequency, type of content, and device of choice), vision (normal/corrected), disabilities (learning or reading), state (under the influence of drugs, medications, and 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 (Figure 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 (Figure 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 five fonts. Assignment of fonts to passages was randomized per participant. The five 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]), 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

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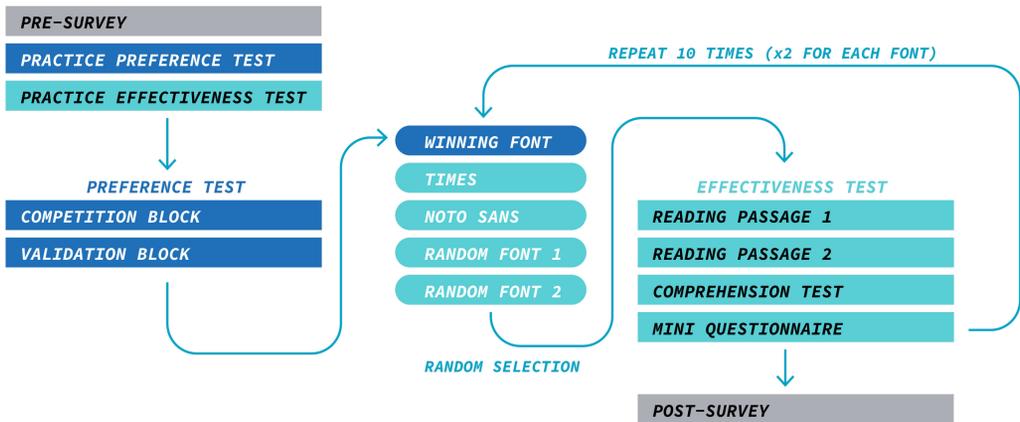
Fig. 9. Apart from a pre-survey to gather demographic information and reading experience, and a practice session, this study design consists of two distinct phases. In the first phase, participants complete a preference test: a double-elimination tournament with 16 fonts, leading to 30 pairwise comparisons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

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; and (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 **words-per-minute** (**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 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

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[13]We removed reading speed measurements outside of the 100–650 WPM threshold before applying IQR for data removal.

statistical methods (Section 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 at recruiting 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 30–39 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 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 five fonts they read in. We treated this as an implicit pairwise comparison by sampling each pair of fonts out of the five 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 two sets of passages per font and answered two multiple-choice comprehension questions per passage (selecting out of three possible answers per question). When we report comprehension score as a percentage, it is based on a total of four 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 Figure 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_β 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_β 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_β 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 are 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_β 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).

	Most Preferred	Win Rate	Avg Elo Rating	Elo Disagreement	Speed Rank	WPM	WPM Standard Deviation	Comprehension	Font Familiarity	For Each Column
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 six and bottom six fonts according to each metric are color-coded blue and orange, respectively (with darker colors at the extremes).

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

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 ≥ 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
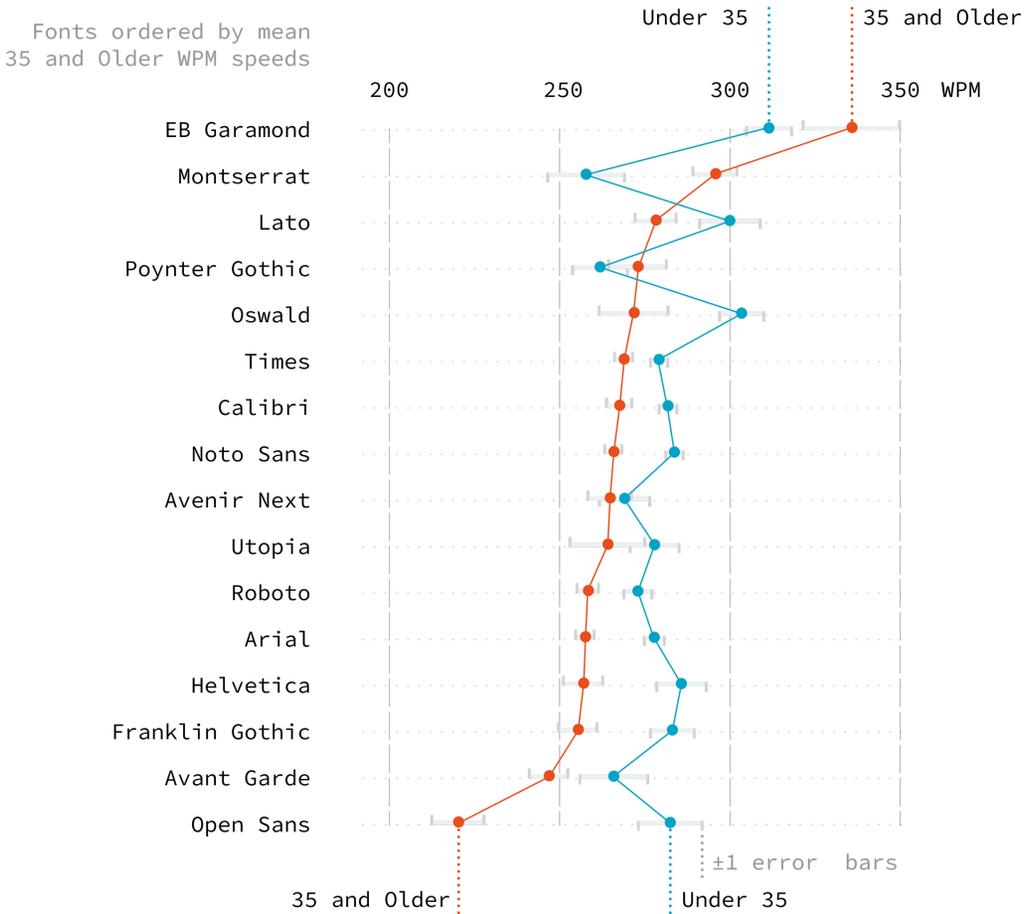
Fig. 11. Mean reading speed (in WPM) per font across participants separated by age, with participants under 35 in blue, and all others in orange. Error bars represent ±1 within-participant standard error. Group sizes vary by font exposure, but total N = 118 for older participants and 234 for younger. 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.

age of participants increased, especially after 35 years. Regarding fonts, when considering just the older participants (age ≥ 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.

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

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.

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 (Figure 12).

6.2.1 What Gains in Reading are Achievable by Font Choice? At the individual level, there appear to be effective fonts for participants(Figure 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.

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 (Figure 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

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[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.

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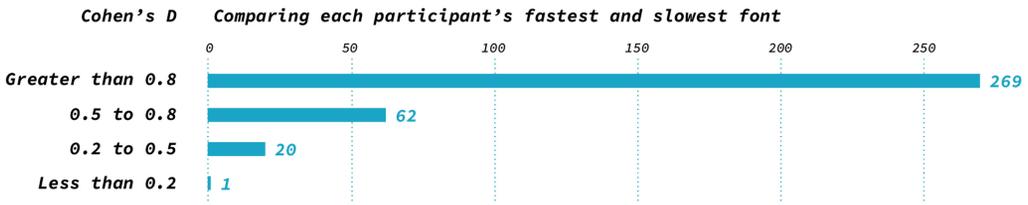
Fig. 13. This histogram bins the effect sizes computed using Cohen's *d* when comparing the fastest and slowest font per participant. Only one participant did not show at least a small effect size when considering reading speed as a function of font.

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 (Figure 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 (Figure 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, three 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
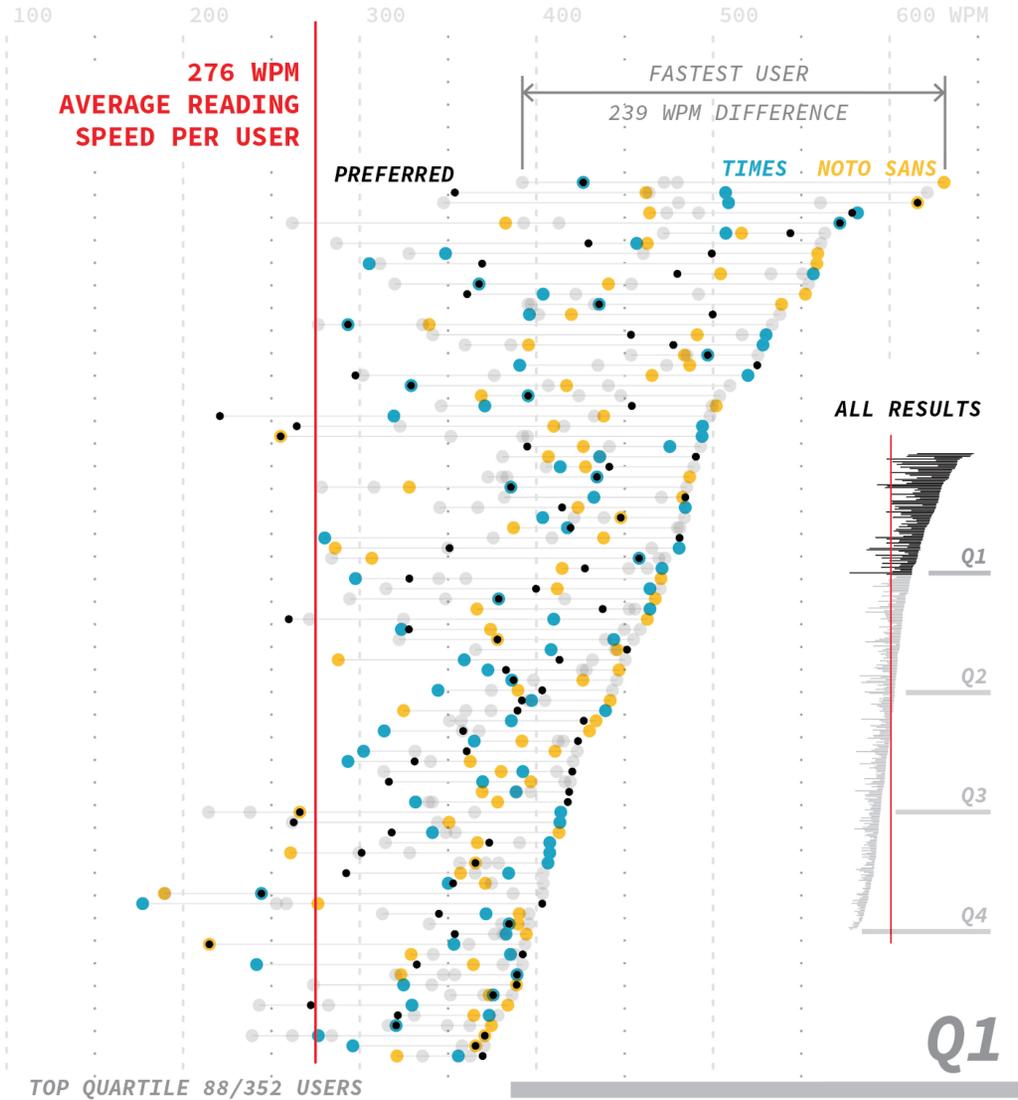
Fig. 14. The fastest readers (top quartile) show the potential that a single manipulation, font, can have on reading speed. Each row represents one participant, with the reading speeds achieved in five different fonts plotted as color-coded circles: preferred font (black), Times (blue), Noto Sans (yellow), and another two-three 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.

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
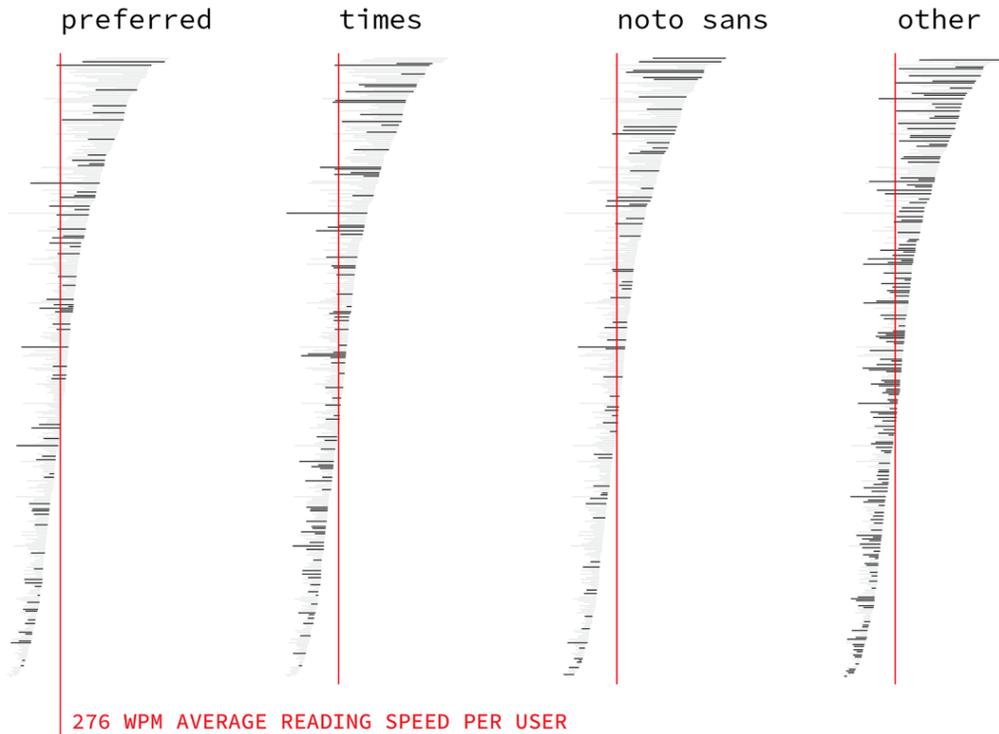
Fig. 15. This figure contains another view of the data from Figure 14, zoomed out and replicated four times to show that different participants read fastest using different fonts. The label at the top of each plot is one of the study's conditions for reading speed: a participant's most preferred font, 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).

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

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, and Calibri) performing consistently better than in our previous study [107]. As a notable example, Times, which was in the bottom five fonts according to Elo Rating in our previous study, is in the top five fonts in the present study. In contrast, participant preferences for Noto Sans were relatively stable across both studies. It was in the top five 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 Figure 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 article.

— 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 Toward 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

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

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 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 United States. 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 article 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–10 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 2 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 are 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.

APPENDICES

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 at minimizing 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 1,500 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

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

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%

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 three 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_β = 0.001; p = 0.009), reading device (p = 0.010; tablet = 213 WPM, phone = 223 WPM, laptop = 249 WPM, and desktop = 267 WPM), participant age (−1.2 WPM/year; R^2_β = 0.018; p = 0.001), font familiarity (R^2_β = 0.002; p = 0.003), and topic familiarity (R^2_β = 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_β = 0.025; p < 0.001), passage order (2.4 WPM/passage; R^2_β = 0.003; p < 0.001), whether the passage was fiction (fiction passages were read 26 WPM faster than non-fiction; R^2_β = 0.013, p < 0.001), and topic familiarity (R^2_β = 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_β 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 an R_m^2 of 0.081 and an R_c^2 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.

Table 2. Analysis of Deviance Table (Type II Wald X^2 Tests) Showing the Effect of Model Predictors on WPM Across All Participants

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

*Represents that the result was statistically significant.

Table 3. Effect Sizes Measures Calculated as R_β^2 and Standardized β for All Significant Model Coefficients

Effect	R_β^2	Standardized β
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 4. VIFs Calculated to Check for Multicollinearity

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

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 an R^2_m of 0.128 and an 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.

Table 5. Analysis of Deviance Table (Type II Wald X^2 Tests) Showing the Effect of Model Predictors on WPM Across Older Participants

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

*Represents that the result was statistically significant.

Table 6. Effect Sizes Measures Calculated as R^2_β and Standardized β for All Significant Model Coefficients

Effect	R^2_β	Standardized β
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

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.

Table 7. Variance Inflation Factors (VIFs) Calculated to Check for Multicollinearity

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

A VIF of >5 is an indication of high multicollinearity.

The model has an R_m^2 of 0.098 and an 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.

Table 8. Analysis of Deviance Table (Type II Wald X^2 Tests) Showing the Effect of Model Predictors on Comprehension Scores Across All Participants

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 *

*Represents that the result was statistically significant.

Table 9. Effect Sizes Measures Calculated as R_β^2 and Standardized β for All Significant Model Coefficients

Effect	R_β^2	Standardized β
Passage Interest	0.0188	1.1456
Non-Fiction	0.0176	1.1707

Table 10. VIFs Calculated to Check
for Multicollinearity

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

A VIF of >5 is an indication of high multicollinearity.

H.4 Comprehension: Older Participants

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

The model has an R_m^2 of 0.653 and an 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.

Table 11. Analysis of Deviance Table (Type II Wald X^2
Tests) Showing the Effect of Model Predictors on
Comprehension Scores Across Older Participants

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 *

*Represents that the result was statistically significant.

Table 12. Effect Sizes Measures Calculated as R_β^2 and
Standardized β for All Significant Model Coefficients

Effect	R_β^2	Standardized β
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 13. Variance Inflation Factors (VIFs)
Calculated to Check for Multicollinearity

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

A VIF of >5 is an indication of high multicollinearity.

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.

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

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 *

*Represents that the result was statistically significant.

Table 15. Effect Sizes Measures Calculated as R^2_β and Standardized β for All Significant Model Coefficients

Effect	R^2_β	Standardized β
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 16. VIFs Calculated to Check
for Multicollinearity

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

A VIF of >5 is an indication of high multicollinearity.

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 an R_m^2 of 0.051 and an R_c^2 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.

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

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

*Represents that the result was statistically significant.

Table 18. Effect Sizes Measures Calculated as R_β^2 and
Standardized β for All Significant Model Coefficients

Effect	R_β^2	Standardized β
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 19. VIFs Calculated to Check
for Multicollinearity

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

A VIF of >5 is an indication of high multicollinearity.

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 (Figure 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

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

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%

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.

Table 21. Reading Speed Matchups Part 1

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%

(Continued)

Table 21. Continued

Font 1	Font 2	Times Read	How often was Font 1 faster?
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%

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.

Table 22. Reading Speed Matchups Part 2

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%

(Continued)

Table 22. Continued

Font 1	Font 2	Times Read	How often was Font 1 was faster?
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%

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

Paper	Year	Language	Font *Speed*	Size *Speed*	Age *Speed*	Preference *Speed*	Familiarity *Speed*	Serifs *Speed*	Italics *Speed*	Font *Preference*	Size *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
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 Wallace	2020 Wallace	2019 Chatrangsan	2018 Wang	2016 Rello	2016 Rello	2013 Beier	2011 Bhatia	2011 Banerjee	2008 Beymer	2005 Darroch	2003 Bernard	1998 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 one font each, and to the best of our knowledge did not disclose the fonts they used.

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