We present Marvista—a human-AI collaborative tool that employs a suite of natural language processing models to provide end-to-end support for reading online articles. Before reading an article, Marvista helps a user plan what to read by filtering text based on how much time one can spend and what questions one is interested to find out from the article. During reading, Marvista helps the user focus on one paragraph at a time and reflect on their understanding of each paragraph with AI-generated questions. After reading, Marvista generates an explainable human-AI summary that combines both AI’s processing of the text, the user’s reading behavior, and user-generated data in the reading process. In contrast to prior work that offered (content-independent) interaction techniques or devices for reading, Marvista is the first human-AI collaborative tool that contributes text-specific guidance (content-aware) to support the entire reading process.

**ABSTRACT**

We present Marvista—a human-AI collaborative tool that employs a suite of natural language processing models to provide end-to-end support for reading online articles. Before reading an article, Marvista helps a user plan what to read by filtering text based on how much time one can spend and what questions one is interested to find out from the article. During reading, Marvista helps the user focus on one paragraph at a time and reflect on their understanding of each paragraph with AI-generated questions. After reading, Marvista generates an explainable human-AI summary that combines both AI’s processing of the text, the user’s reading behavior, and user-generated data in the reading process. In contrast to prior work that offered (content-independent) interaction techniques or devices for reading, Marvista is the first human-AI collaborative tool that contributes text-specific guidance (content-aware) to support the entire reading process.

**CCS CONCEPTS**

- Human-centered computing → Interactive systems and tools.

**KEYWORDS**

keyword1, keyword2, keyword3, keyword4

*Reading is not memorizing paired associates. It requires much more complex psychological processes of strategic search, organization for remembering, use of natural units in problem solving, the discovery of rules and order, and the economical use of them.*

—Gibson & Levin, The Psychology of Reading.

1 INTRODUCTION

Reading is a universally important activity that can also be challenging for many of us, as articulated in the above passage from [13]. Currently 43 million US adults possess low literacy skills (< level 2) and even for people who can comprehend text, they might struggle to “truly understand and appreciate what the text is saying” [15, 42]. The growing consumption of online media might have exacerbated such challenges, as online media often comes in small bits that encourage “rapid, distracted sampling” while weakening our ability to focus, read, and think deeply [7], especially when the amount of information, such as long articles, goes well beyond social media posts. As people are reading an increasing amount of text online [41], the above studies suggest opportunities to provide guidance that helps readers more strategically navigate and comprehend text.

To support people’s reading activities, past work has been studying and comparing how people read on different platforms [31, 36], leading to a plethora of interaction techniques [9, 16, 28, 29, 43] and devices [2, 18, 38, 53] that support active reading, i.e., reading combined with “critical thinking and learning” by directly manipulating or annotating text. However, the problem is that, even provided with such techniques or devices, people performing active reading are still faced with the aforementioned challenges due to a lack of guidance with respect to the specific text a person is reading. For example, a reader might not know how to strategically navigate the text given their specific interest or limited time constraints. As people are increasingly overwhelmed by the amount and diversity of online information, it is important to complement active reading techniques with text-specific guidance so that a reader can gain more value in this process.

In this work, we designed and implemented Marvista—a human-AI collaborative reading tool that employs a suite of natural language processing (NLP) models1 to understand the text and then to provide guidance for the reader throughout the whole reading process. Figure 1 showcases a typical interaction scenario using Marvista integrated as a browser extension.

Before reading an article, Marvista helps a reader plan a high-level reading strategy using two filtering techniques: (i) The time filter allows the reader to specify how much time they would like to spend (Figure 1a), based on which Marvista highlights the most summative subset of the text to read that stays within the user’s time budget; and (ii) The question filter allows the reader to select from a list of AI-generated questions (Figure 1b) that can be answered by reading the article, based on which Marvista highlights the corresponding text that contain the answers (Figure 1d).

During reading the article, the focus mode of Marvista modifies the display to let the user read the article one paragraph at a time (by “dimming” the other elements on the page, as shown in Figure 1c). In this way, Marvista can also infer the user-perceived importance of each paragraph by recording how much the reader spent dwelling on that paragraph2. Besides the common active reading features of highlighting and note-taking, a Marvista user can also reflect on their understanding by answering an AI-generated question about a paragraph (Figure 1e).

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1Hereafter interchangeably referred to as ‘AI’.

2Currently, Marvista only records dwelling time on each paragraph, which would inevitably include time of non-reading activities.
Figure 1: Marvista supports the entire reading process: Before reading, Marvista helps a user plan what to read by filtering text based on how much time one can spend (a) and what questions one is interested to find out (b, d). During reading, Marvista helps the user focus on one paragraph at a time (c) and reflect on their understanding of each paragraph with an AI-generated question (e); After reading, Marvista generates a human-AI summary (f) that combines both AI’s processing of the text, the user’s reading behavior, and user-generated data (g); hovering over a sentence (f) explains which paragraph it is related to and why including its information in the summary (h).
After reading the article, Marvista generates a human-AI summary (Figure 1f) that combines both AI’s processing of the article’s text as-is and the user’s perceived importance of each paragraph, which is computed from their dwelling time (implicit behavior), and user-generated data, including notes and highlighted text (explicit behavior). The user can adjust how much each factor should influence the human-AI summary (Figure 1g). Further, the summary is explainable: the user can hover on each sentence in the summary to see how it can be attributed to the specific text in the article or the specific user-generated data that leads to certain text being included in the summary (Figure 1h).

We evaluate Marvista in our main study where 17 participants open-endedly used Marvista to read science and technology articles of their choice from the PopSci website. The goal was to probe how people would interact with, think of, and benefit from Marvista’s human-AI collaborative reading features. We found that (i) participants used Marvista to better understand not only the text they read but also how they read the text; (ii) Marvista’s different features are better fits for some reading scenarios but not for the others; (iii) Participants found Marvista different from how they normally read; and (iv) One challenge was to interpret Marvista’s output with limited context; and (v) Instead of unconditionally trusting (over-relying) AI, multiple participants were able to identify issues with the model.

Further, we conducted a small-scale follow-up study using two tasks’ output as indicators of over-reliance on Marvista. Specifically, participants read a set of three articles on ‘diet’, wrote a summary for each article (Task 1), and wrote a personal review at the end (Task 2). We found mixed results: (i) There was no statistical significance (except for one article) to support that Marvista participants’ article summaries were more similar to AI-generated summaries (nor less similar to human-written summaries) than the Baseline participants’; however, (ii) Marvista participants’ personal reviews were significantly more similar to one another than the Baseline users’, indicating an influence by Marvista that might lead to over-reliance.

The main contribution of this work is that we designed and developed, to our best knowledge, the first human-AI collaborative reading tool. In contrast to previous tools that offer generic interaction techniques (content-independent), Marvista serves as a “reading buddy” who employs a suite of NLP models to provide text-specific guidance (content-aware) throughout the whole reading process, from planning a custom reading strategy, to focusing, annotating, and reflecting on one paragraph at a time, and to generating a personalized, explainable human-AI summary after reading the article.

2 RELATED WORK

As a human-AI collaborative reading tool, Marvista is related to two schools of prior work: human-AI collaborative systems and tool support for reading.

2.1 Human-AI Collaborative Systems

The high-level principles of designing human-AI collaborative systems are discussed in early work. For example, Terveen characterizes two major approaches of humans collaborating with computers: (i) the human emulation approach where computers are built with “human-like abilities to enable them to act like humans” and (ii) the human complementary approach that leverages computers’ “unique abilities, to complement humans” [44]. Horvitz lays out principles of designing mixed-initiative interaction where humans and agents take turns to jointly accomplish a task [19]. For example, whether an agent takes initiative should be determined by considering both the utility of the action against the uncertainty of the inferred user intents. A plethora of later work instantiated these principles into the design of specific interactive systems, which, for presentation purposes, we organize into the following non-mutually-exclusive categories.

(i) AI can take a user’s partial input and continue with the rest of the task that would otherwise be manual and possibly tedious. For example, Chateau is a 3D sketching interface that observes what has been drawn and predicts a user’s next drawings or provides suggestions to complete their current drawing [21]. Tsang et al. search for images similar to a target design to guide the creation of 3D curves and suggest relevant geometry based on users’ input strokes [46]. In the domain of writing, numerous text entry techniques employ language models to autocomplete a user’s typing [27] and recent developments in neural networks further enable ‘smart compose’—AI that can autocomplete a user’s partially written sentence [8] or improve writing skills [20].

(ii) AI can filter, transform, or perform analyses of a large amount of data so that humans can examine the data more efficiently to obtain more insights. Wang et al. interviews data scientists to learn their attitude towards AutoAI—AI that can potentially automate what data scientists do by analyzing data and creating preliminary models from data [50]. Similar to data scientists, medical professionals are also faced with challenging scales and complexity of data. Tschandl et al. compare how different types of AI-generated information can help or affect physicians’ diagnosis behavior/outcome in a skin cancer domain [47]. Gu et al. found that pathologists benefited from AI-suggested regions to start the examination of a histological slide [14]. On the other hand, when AI algorithms cannot retrieve clinically meaningful past medical images, physicians’ input can help filter and refine the results so that the examples are more relevant to a present case [6].

(iii) AI can offload low-level computational subtasks based on high-level goals specified by humans. For example, in Umetani et al.’s furniture design tool, as users edit a design, the tool indicates structures that are non-durable and/or non-stable, and further offers suggestions for solving these problems [48]. DreamSketch enables users to sketch their ideas (e.g., the seating of a glider) while leaving structural components (e.g., connectors between seats, handles, and wings) to be generated by an optimization module [22]. Willett et al. develop a tool for turning static images into animation where the automated algorithm is guided by a small amount of user input (e.g., which objects to animate, the trajectory, and depth information) [51]. Forte is a tool where an optimization algorithm follows a user’s rough sketch to generate structural designs and addresses

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https://www.popsci.com
their preference such as how much the design can deviate from the initial input [10].

Marvista’s human-AI collaborative support for reading mostly resembles the second approach—AI processes text before, during, and after reading to help users read in a more efficient, focused, and informed manner; meanwhile, users’ reading behavior and generated data helps AI provide more personalized support, e.g., generating a human-AI summary that addresses a reader’s interest (as dwelling time) on each paragraph.

2.2 Tool Support for Reading
Reading on digital screens (as opposed to on physical papers) was a relatively recent development that has been a result of increasingly democratized personal computers from laptops to tablet devices. To support screen reading, several studies have attempted to understand people’s reading behavior from the physical to digital domains. O’Hara surveys literature to construct a typology of reading: how people read, what they do besides reading, and why they read [35]. Specifically, this typology incorporates Lunzer’s taxonomy of four reading types (receptive, reflective, skim, and scan) [26], Anderson & Armbruster’s categorization of reading support activities (underlining, note-taking, outlining, and networking) [1], and Robinson’s SQ3R technique (survey, questions, receptive/recital/review) [40]. A follow-up study by O’Hara and Sellen compared the difference of reading on physical papers vs. digitally on a screen and summarized users’ behavior and experience in terms of annotation, navigation, and layout [36]. This study was later revisited by Morris et al. with additions of new reading media (horizontal display with pen input and multiple tablets) [31].

All these studies gave rise to a series of interactive devices and techniques that support active reading on digital media. The term ‘active reading’ refers to “a broad set of cognitive skills and activities, such as thinking, learning, note-taking, annotations, searching and skimming, that enable an individual to achieve a deep level of comprehension of a document” [3]. One of the earliest active reading tools is XLibris—a hardware/software platform that supports active reading via three main features: a digital tablet for reading scanned images of papers, a “Reader’s Notebook” to collect excerpts of text, and capabilities to search for similar parts of the document based on highlighting and annotations. The popularization of touch devices led to several designs, such as LiquidText—a tablet-based reader that employs a suite of multi-touch gestures to address specific problems in reading text on physical papers, such as organizing and synthesizing annotations and reading disparate parts of the document in parallel. Hinckley et al. present touch-based techniques for informal information gathering (e.g., cropping a paragraph, collecting multiple pieces of images/text) that are designed to be lightweight and to not disrupt the flow of reading [17]. Mehta et al. study and develop tool support for literary critics to perform “close reading” of text where each reading connects to and builds on the previous ones and external resources are often drawn on to facilitate the interpretation [29]. Some research employs multiple types of devices for reading. Chen et al. design a multi-slate reading environment that mimics how people’s reading activities often benefit from multiple spatially-distributed physical papers [9]. Matulic and Norrie incorporate pen input together with touch to support navigation and in-document search [28]. In the meantime, some research has invented new device components to support active reading. Bianchi et al. design and build a physical reading aid for digital tablets that mimics a physical bookmark yet provides a suite of interaction techniques to support active reading [2]. Yoon et al. explores the sensing of grasp when using tablet devices to design techniques that enhance active reading for and across individuals [53].

In contrast to prior work on techniques and devices that are content-independent (i.e., the proposed interactions with reading materials are independent of the actual contents—what the text is written about), Marvista aims to provide content-aware support for active reading by helping users process text throughout the whole reading process.

3 DESIGN & IMPLEMENTATION
In this section, we describe Marvista’s key features spanning three phases: before, during, and after reading an article.

3.1 Before Reading
Psychologist Eric Lunzer differentiated receptive vs. skim reading in the following way [26]: taking the receptive approach, one reads the text sequentially “as approximating listening behavior” whereas skimming requires a decision-making process about which parts of the text are worth reading. Unfortunately, at present there is little support for a reader to skim the text based on their specific constraints or interests. As a result, readers often attempt to receptively read most of the text only to find out they do not have time to finish it or that there are only specific parts that actually interest them. To fill this gap, Marvista employs NLP models to filter the text based on two user-defined criteria, which provides extra value in the active reading process by helping a user plan strategically what to read.

3.1.1 Time filter. As shown in Figure 2a, as a reader selects the time filter, Marvista first estimates the total amount of time required to read the entire article. Then the reader uses a slider to specify up to how much reading time they would like to spend and Marvista will select and highlight a subset of the text in blue (Figure 2b) that the system considers as must-read given the time constraint.

Design rationale: By allowing a reader to decide how much time they want to spend on reading (while still covering the most important content), the time filter intends to bridge the gap between the effort of reading the full text and people’s limited ability to commit to such effort, e.g., when reading an article is part of a time-sensitive task or when the reader simply does not have the attention span for the whole article.

Implementation: Marvista estimates the total reading time $T$ of an article based on an averaged reading speed of 150 words per minute$^4$. The reader’s specified time limit $t$ is used to compute a compression rate $t/T$, which then serves as a parameter for an extractive summarization model that ranks all input sentences [30].

$^4$We currently use an average reading speed, although the system can be easily extended to let the user specify their own reading speed. The 150 words per minute was a little lower than that in other studies (e.g., 200-250, as reported in [45]) to consider that our current reading materials—science and technology articles—might be more difficult to read.
During the training process, the extractive summarization model utilizes a BERT model [12] for text embeddings and K-Means clustering to identify sentences closest to the centroid for each of the annotated summary sentences. The extractive summarization model will then return a set of sentences which are a subset of the source article and whose total length is equal to or smaller than $\frac{C}{T}$ of the entire text’s length.

### 3.2 During Reading

Complementing existing active reading techniques that allow a user to generate contents (text annotations or notes), Marvista provides additional value by guiding a user to focus on one paragraph at a time and to reflect on the specific contents of a focused paragraph.

#### 3.2.1 Focused mode

As shown in Figure 4, Marvista’s focus mode displays one paragraph at a time while making the other paragraphs and UI elements translucent. A reader can use up/down arrow keys to go to the next or previous paragraph. The reader can also click ‘Pause/Resume’ (top right of the screen) to switch between the focused mode and the normal view of the article.

**Design rationale:** The goal of this design is two-fold: (i) To facilitate a more focused way of receptive reading [26, 40]. By seeing only one paragraph at a time and having to explicitly navigate to the

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**References:**

1. Marvista: A Human-AI Collaborative Reading Tool
2. Marvista: A Human-AI Collaborative Reading Tool
3. Marvista: A Human-AI Collaborative Reading Tool
4. Marvista: A Human-AI Collaborative Reading Tool
5. Marvista: A Human-AI Collaborative Reading Tool
6. Marvista: A Human-AI Collaborative Reading Tool
next one, a reader is made more aware of what they are currently reading and less distracted by the other visual elements\(^5\). (ii) To estimate how much time a reader spends on each paragraph, which later will be used to generate a personalized human-AI summary (detailed in §3.3.2) that emphasizes each paragraph proportionally to the time spent by the particular reader. Such a human-AI summary is akin to the reader’s ’book report’ of the article because it represents which parts of the text the reader actually spends more time on.

**Implementation:** Marvista follows site-specific rules (i.e., HTML selection queries) to extract HTML elements that correspond to paragraphs of an article. Reading time is tracked and accumulated for each paragraph whenever that paragraph is in focus, which includes both reading as well as time spent using the accompanying tools (described below).

### 3.2.2 Reflection

As shown in Figure 5, as a reader focuses on a paragraph, Marvista provides three tools to support active reading, including two common tools for highlighting and note-taking as well as a novel AI-enabled feature—reflection. As a reader clicks the reflection button, Marvista generates a question about the current paragraph (e.g., “What did the scientist say about Omicron?”) for the reader to answer by reflecting on what they have read in the paragraph.

**Design rationale:** The design of this feature is informed by one of Lunzer’s taxonomized reading types called **reflective reading** [26], which “involves interruptions by moments of reflective thought about the contents of the text”. Currently we do not show the answer to the reflective question so that a reader cannot just directly reveal the answer without going through the reflection process.

**Implementation:** We employ the same QG model as the one used in the question filter feature, except now we generate only one question using the extractive summary of the focused paragraph as the answer.

### 3.3 After Reading

Even after finishing the active reading of an article, Marvista continues to provide value to a user by reviewing what they have read via an AI-generated or a Human-AI summary, both of which provide explanation to further help the user understand how certain text is emphasized in the summary.

#### 3.3.1 AI-generated summary

As a reader clicks the “Finish” button, Marvista first generates a summary using an abstractive summarization model. While extractive methods summarize text using a subset of its sentences, an abstractive summarizer generates new (and often shorter) text that carries the most important information from the original text.

**Design rationale:** This feature allows AI to assist the reader with the “review” step in Robinson’s SQ3R technique [40]. We also envision that such a summary would help the reader recall the important information when they revisit the article later. Currently, Marvista saves the most recent reading session and, instead of re-reading the article, a returning reader can choose to directly go to the summary page (by clicking ‘Past Summary’ as shown in Figure 3a).

**Implementation:** Marvista uses the standard Transformers [49] encoder-decoder architecture to generate an abstractive summary as the encoder, uses RoBERTa [24] as the decoder, and then fine-tunes the summarizer on the CNN/Daily Mail [33] summarization dataset with a cross-entropy loss. We use Longformer because it can take eight times more tokens as input than the commonly used BERT encoder, which handles long articles better.

#### 3.3.2 Human-AI summary

Beyond the aforementioned one-size-fits-all summary, Marvista further allows the reader to personalize the AI-generated summary based on two sources of user-generated data from the reading process:

- **Implicitly-generated user data,** for which we use the reader’s dwelling time on each paragraph to weigh its importance. To factor in different lengths across paragraphs, we calculate reading speed for each paragraph (number of words divided by dwelling time): the more time a reader spends per word in a paragraph, the more likely that paragraph will contribute to the generated summary;
• Explicitly-generated user data, which includes the reader’s notes and highlighted sentences as additional contents to the original text. The combined text is then fed to the model to produce an abstractive summary.

A shown in Figure 6b, for each type of user-generated data, the reader can choose a level of impact on the summary: none, low, or high.

**Design rationale:** Dwelling time at the word level has been used in prior work for training a model to estimate a reader’s interest on unseen text [40]. Analogously, Marvista uses dwelling time at the paragraph level to measure a reader’s interest and enables them to see their interested paragraphs emphasized in the summary. Annotation (e.g., highlighting and note-taking) is an integral part of the active reading process [35], yet such user-generated data is often scattered across the documents. Marvista’s human-AI summary feature allows the reader to see their notes and highlighted sentences integrated into the summary.

**Implementation:** To incorporate dwelling time into the summary, we normalize the aforementioned reading speed and map it to weights for each paragraph. We then “hijack” the abstractive model with these weights by element-wise multiplying them to the latent encoder representations of each paragraph before they are fed to the decoder. Note that in this way we can manipulate output summary by adjusting its encoder’s latent space implicitly without the need to collect personalized summaries as training data.

To determine the range of weight values, we conducted an experiment using a small corpus of text from three articles. Given the paragraphs of an article, we gradually increased the weight of one paragraph \( P \) from 0 with a step of 0.1 while fixing the others’ weights as 1. We then computed the ROUGE score [23] as a similarity metric—between the generated summary and \( P \), and found that the score increased/decreased with the weight but flattened below 0.6 and above 1.4. Thus we use \([0.6, 1.4]\) as the range, i.e., an unread paragraph will be weighed as 0.6 and the paragraph with the highest time per word as 1.4. Currently, we use an exponential mapping from time-per-word to weight so that paragraphs with greater dwelling time would stand out more and vice versa.

To incorporate notes and user-highlighted sentences, we simply insert each note or highlighted sentence as new paragraphs immediately after the original paragraph wherein they were generated. Then such user-generated data is treated identically as the other paragraphs by the summarization model. The three levels of impact are mapped to specific weight values for the paragraphs of highlights or notes: none=0.6, low=1.0, and high=1.4.

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**Explanation of summary.** As shown in Figure 6c, as a summary is generated, the reader can check the box of ‘hover to see explanation’ feature (Figure 6b). Then, as they hover over a sentence in the summary, Marvista locates the source of text (or user-generated data) and describes how it is correlated with the summary sentence in the explanation bubble.

**Design rationale:** The goal of such explanation feature is two-fold: (i) to create a feedback loop so that the reader can see that the summary indeed incorporates user-generated data as they specify; and (ii) to serve for indexing purposes so that the reader can use the generated summary as a “portal” to access specific reading history, notes, and highlighted text.

**Implementation:** We employ a post hoc similarity-based approach to generate such explanations. Given a hovered sentence \( S \) in the summary, we compute the ROUGE score [23] between that sentence and each one of the original paragraphs, user-generated notes, and user-highlighted sentences\(^6\). If the highest score is between \( S \) and an original paragraph, we first check its dwelling time (per word): if it is above the average, we report in the explanation “You spent more time (per word) in this paragraph than X% of the other paragraphs”; otherwise, we show in the explanation bubble “This paragraph is the most related.” If the highest score is between \( S \) and a note or a highlighted sentence, the explanation bubble shows “You wrote a related note here: [the note]” or “You highlighted a related sentence here.”

4 **MAIN STUDY: PROBING HOW USERS OPEN-ENDEDLY INTERACT WITH MARVISTA**

In contrast to prior work on content-independent techniques, Marvista leverages AI to provide content-aware support throughout the whole reading process. To understand how users might react to and make use of such a novel human-AI collaborate reading tool, we conducted an open-ended study to probe users’ reading behavior while interacting with Marvista. This study was approved by our Institutional Review Boards (IRB).

4.1 **Participants, Tasks, & Procedure**

We recruited 17 participants (nine males and eight females, aged between 20 and 39) from a local university. There were six undergraduate, three master, and eight doctoral students, majoring in Electrical & Computer Engineering and Mechanical Engineering.

The study was conducted in person\(^7\). We first went through the informed consent process with each participant, including an explanation of the kinds of data that would be collected, i.e., audio and screen recordings and their usage log of interacting with our tool. Specifically, the log consisted of mouse/keyboard input events and user-generated data (e.g., their answers to reflective questions), which would be stored in the browser’s cookie and deleted after we processed the raw data after each study session. Once the briefing was completed, we started with each participant watching a tutorial video to learn how to use Marvista, which took about five minutes. Next, they would spend about 25 minutes using Marvista to freely explore and read any articles on the Pop Science website. We chose this website because science and technology articles have been commonly used for studying reading behaviors in past research [52]. Participants used a Google Chrome browser to read articles that were displayed on a 13” laptop computer. All the NLP models ran on a separate networked server. Finally, we conducted a 30-minute interview to gather participants’ feedback on each of Marvista’s key features. Each study session lasted for about an hour and each participant was compensated with a $25 Amazon gift card for their time.

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\(^6\)Unless the impact level is set to none for the latter two factors.

\(^7\)We conducted this study in-person in part due to the need of ensuring stable and fast network connection that was necessary for our tool to communicate with the back-end server. At the time of the study, our institution was already open for in-person attendance and we followed regulations throughout the studies such as in-door masking requirements.
4.2 Measurement & Analysis

We recorded the screen and audio of the whole process. Integrated with Marvista, we logged participants’ tool usage data, e.g., which articles they read, how much time they spent on each article, and how often they interacted with each feature (detailed in §4.3). We analyzed this quantitative data in two folds: an overall analysis that computes the distribution of several key metrics and a phase-specific analysis that further looks into how participants interacted with Marvista’s features before, during, and after reading an article.

During the interview, to gain further insight behind how participants used Marvista, we asked them to rate each of Marvista’s key features (shown later in Table 1) based on the following two questions: (i) Does this feature provide extra value to your reading experience (1: not at all → 7: highly valuable)? If so, what are the use cases? (ii) Does this feature require extra effort in addition to reading the article (1: not at all → 7: high effort)? If so, describe the effort. For the qualitative data, we employed the thematic analysis approach [4]: the first author transcribed participants’ responses to formulate the initial codes, which were then reviewed by two other authors. Then, disagreements were resolved via discussion between the authors.

Below, we report two sets of findings: statistics that characterize participants’ reading behavior using Marvista (§4.3) and their qualitative feedback on Marvista (§4.4).

4.3 Findings: Reading Behavior Using Marvista

4.3.1 Overall statistics. As shown in the histograms8 in Figure 7, participants read an average of 3.8 articles (Figure 7a) and the average length (word count) of the articles was 928 (Figure 7b). On average, each article was read 1.9 times (each time is called a session): as shown in Figure 7c, most participants read an article up to two times, although a small number went as high as six or more times. Participants spent on average five minutes four seconds on each article (or two minutes 39 seconds per session): as shown in Figure 7de, the time-spending patterns per article and per session exhibit a ‘long tail’ with the majority on the lower end. When using the focus mode, we tracked which paragraph was actually being read and calculated the percentage of an article actually being read by a participant, which was on average 64.0% (Figure 7f); while a majority did read the entire article while using the focus mode, quite a number of sessions did not involve any reading at all. Upon further analyses, we found that amongst the 29 such no-actual-reading sessions, participants skipped to the summary 12 times by hitting the ‘Finish’ button, another 12 times they hit the ‘Quit’ button (which would lead them to the before-reading state of the tool), and in the remaining five times the page was redirected elsewhere (e.g., going back to the main page or opening a hyperlink).

4.3.2 Usage of before-reading features. Before a reading session of an article, participants filtered the text by time 41.1% of the time, by question 35.5% of the time, and without using either filter 23.4% of the time. For each participant, we calculated their average number of time and question filter usages per article and show the distributions in Figure 8ab. When using the question filter, participants selected an average 39.2% of the questions generated by Marvista (by default no questions were selected). When using the time filter, the reading time set by the participants was on average 57.6% of the estimated time of reading the entire article, which is not surprising considering the default setting was 50.0%.

To further analyze the effect of the time filter, for each reading session, we compare the reading time set by a participant and the actual time spent in that session. Figure 8c showed the results: we can see that overall participants tended to spend less time than they had set using the time filter. To understand whether the time filter did help participants save time, we compare time spent on sessions using the time filter vs. using no filter. On average, participants spent two minutes 30 seconds per 1000 words when using the time filter vs. four minutes with no filter. In other words, participants spent 37.5% less time on articles when using the time filter.

4.3.3 Usage of during-reading features. Participants used the focus mode 92.0% of the time. We hypothesize that the focus mode being the default setting might have contributed to such high frequency of usage but will need to verify that with further studies (e.g., using an A/B testing setup). Overall, participants did not use the active reading features very often. The average number of usages per article were 1.2 for highlight, 0.9 for note, and 1.2 for reflection. Figure 9 shows more details about participants’ distribution in their usage of the three features (per article). In particular, unlike highlight and note, there were two avid users of the reflection feature with a significantly higher number of usages (11 and 17 per article).

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8In each of the histograms the Y-axis is the count and the X-axis is a specific measurement.
We discuss the qualitative findings below, organized by features, and summarize recurring themes later in §4.3.

### 4.3 Usage of after-reading features.

By design, participants were always shown an AI-generated summary upon finishing an article; in comparison, about two thirds (67.7%) continued to use Marvista to generate a human-AI summary. The average number of human-AI summaries generated per finished reading session was 1.0 and the distribution across participants is shown in Figure 10a. When choosing which one or more factors to impact the human-AI summary, participants overall seemed to prefer emphasizing dwelling time and highlights, choosing per-paragraph dwelling time in 64.3% of the cases (38.1% low impact and 26.2% high impact), choosing highlights in 64.3% of the cases (36.9% low impact and 27.4% high impact), and choosing notes in 26.2% of the cases (15.5% low impact and 10.7% high impact). Further, upon finishing a reading session, 59.3% of the time participants would seek an explanation of the generated summary (averaged 2.3 explanations per finished reading session). The distribution across participants is shown in Figure 10b.

### 4.4 Findings: Feedbacks to Marvista

Table 1 visualizes participants ratings on each Marvista feature’s extra value vs. extra effort compared with reading without using the tool. After each rating, we asked follow-up questions, including use cases for which each feature would provide extra value, the kinds of extra effort required, and other feedbacks and comments. We discuss the qualitative findings below, organized by features, and summarize recurring themes later in §4.3.

#### 4.4.1 Time filter.

Most participants were able to relate to the need of using the time filter. For example, P4, P5, P9, and P11 mentioned the use case of this feature for reading articles as part of work or study assignments, which requires reading efficiency. P6, P8, and P15 also commented that, by setting a certain amount of time and seeing the corresponding parts of the text, they felt they could better focus on reading. P12 and P13 mentioned the time filter’s usefulness for skipping parts of long articles:

> “... useful for longer articles where the reader has an interest but not enough time to go through the whole article” (P12)

Some participants recognized that such a feature was not always useful, e.g., P5 would not use the time filter when reading for leisure and P15 felt having to read fast was not the usual case for him. Some others pointed out the difficulty of deciding how much time one should choose (P1) and that, for novice users, it might not be clear what it means to read, say, three minutes of a five-minute article (P17). Another issue raised by P3, P8, and P12 was that AI-selected sentences sometimes were out of context and could not be fully understood as-is, which is a limitation of the extractive summarization model, as discussed later in §6.3.6.

As a response to this feature, we also saw two contrastive perceptions of time in reading. P9 and P11 mentioned the pressure they felt to finish the article within the set time even though Marvista did not actually enforce the reading time, while P2 and P15 felt the opposite and would like to see their reading time precisely tracked as they read the article. Such a disparity suggests the need of customized granularity when setting the time filter. For example, in lieu of exact time that might add pressure to some readers, Marvista can provide coarse modes: e.g., quick, normal, or deep read; contrastively, Marvista can optionally add a timer during reading for those who prefer to track the time spent.

#### 4.4.2 Question filter.

Multiple participants (P3, P4, P9, P10, and P15) mentioned that the generated questions were useful and equivalent to the main ideas and key points of the article for them to preview before reading:

> “Helps check understanding. Make[s] sure you’re getting main points. Shows you what to look out for in the article.” (P10)

P7, P11 and P16 also pointed out that this feature was time-saving because a reader could spend their time only on questions that interest them. Further, some participants considered such questions a way to get them thinking about the article:

> “When the article is too long or complicated, I might be a bit confused or unsure about my expectation after reading it. A list of questions give me some insights (and) reminders.” (P2)

> “It primes my mind for the important parts of the article. Gets me thinking right away. It also leads me through the hover feature to the areas of the text where I can find the answer. I also found it efficient because I can isolate the parts of the text and just read the parts associated with the answer.” (P8)

As indicated in the effort rating (Table 1), the main issue brought up by participants was the difficulty/effort of choosing questions because (i) a reader unfamiliar with the article’s topic might find it hard to fully understand the questions (P1), (ii) some questions needed more context (e.g., “What did the scientists find out?”) that was not available before reading (P3 and P17), and (iii) the process
of reading through the questions and determining which ones to include could be effortful (P2, P5, P10, P11, and P15).

4.4.3 Focus mode. Focus mode is the only feature that did not directly rely on AI, yet it was universally well-received by all participants (all ratings on its extra value were neural or above).

“I think it really helped me focus on the specific paragraphs rather than being distracted by other elements.” (P14)

Participants pointed out the value of “visually focusing” (P1) on the current paragraph to avoid being distracted by other elements on the page (P4 and P14), which they considered helpful given that articles could be “less organized” (P9) and contain “a lot of information” (P7). Focus mode makes reading “less overwhelming” (P5) and “… helped to break down the content and make it feel easier to move through.” (P8)

Participants also pointed out this feature’s usefulness when reading in “a crowded room” (P8) or “a distracting environment” (P15). A few also commented that they felt more aware of the paragraph they were reading (P3) and could go into more depth in the focus mode (P10).

While almost all participants perceived no extra effort in using this feature, two mentioned the trade-off of not being able to read the focused paragraph with more context, e.g., looking back to already-read text to find relevant information (P16) or looking forward to skip to a certain paragraph. Another issue was adapting to such a different way of paragraph-by-paragraph reading: participants commented that using the arrow keys felt less natural than just normally using gaze (P2), sometimes causing one to forget to use the keys and just to habitually read the next paragraph without pressing the ↓ key to place it in focus (P5).

4.4.4 Reflection. Seven participants considered this feature useful for helping them check their understanding after reading a paragraph, which they “may have overlooked when reading quickly or getting distracted” (P8). P4 and P7 mentioned that they would use reflection to help them review or re-read a paragraph:

“… to force me to read over a paragraph again, in a more focused way. For example, in the articles I was confused about certain paragraphs, but had a hard time pinpointing my confusion. Reflecton tool gave me a more specific point to look for when re-reading.” (P4)

Meanwhile, three participants stated that they would not use this feature due to a lack of such needs (P17) or when reading “for entertainment or quick info searching … [and not wanting to] spend time answering questions” (P2) or when preferring reading without interruptions (P12).

Multiple participants acknowledged the extra effort in re-reading the paragraph, thinking about and typing in the answers to the reflection question but all considered such effort “worth it” (P5 and P10) and “valuable for improving a user’s understanding of the paragraph” (P13).

One noticeable issue, which was related to the question filter, was the quality of the generated reflection question. P10 commented that some questions focused on a factual detail of a sentence rather than capturing the overall idea of the paragraph and P16 felt some questions did not seem important with respect to the paragraphs. This is a known issue in question generation research in NLP, which we discuss in more technical details in §6.3.6.

4.4.5 AI-generated summary. Participants split on how they would make use of this feature. A number of participants (P1, P2, P5, P10, P14, and P15) considered AI’s summary as an alternative solution to having to read the entire article thoroughly—

“Useful for someone who skims the article and would prefer to see a summary in lieu of a read-through.” (P5)

For some others (P3, P4, P5, P7, and P12), instead of skipping parts of the article, they would use AI’s summary to compare with and check their own understanding of the article:

“As a ‘check your understanding’, for me. I like to have verification of my understanding of content but don’t like answering questions. It’s helpful to read a summary and compare to my understanding” (P4)

The main issue, which was pointed out by seven participants, was the occasional inaccuracy of the model in capturing the gist of the article, which is a known issue in most summarization models. For example, P10 mentioned the summary was “sometimes too trivial” and did not “pick out what I thought to be the most important parts of the article”. However, for these participants, such observed inaccuracy did not discount their perceived usefulness of AI’s summary—they were cognizant that an AI-generated summary’s usefulness came with certain limits and would choose to rely on their own when the AI was inaccurate—

| Does this feature provide extra value? | Does this feature require extra effort? |
|--------------------------------------|---------------------------------------|
|                                      | (1: not at all; 7: highly valuable)   |
| Time filter                          | 1 2 3 4 5 6 7                        |
| Question filter                      | 0 0 2 3 5 0 7                        |
| Focus mode                           | 0 0 0 2 3 5 0                        |
| Reflection                           | 0 0 0 2 3 5 0                        |
| AI-generated summary                 | 0 0 0 2 3 5 0                        |
| Human-AI summary                     | 0 0 0 2 3 5 0                        |
| Explanation of summary               | 0 0 0 2 3 5 0                        |

| Does this feature require extra effort? |
|----------------------------------------|
| (1: not at all; 7: high effort)        |
| Time filter                            | 5 4 5 2 0 1 0                       |
| Question filter                        | 5 4 3 1 3 1 0                       |
| Focus mode                             | 13 1 0 2 1 0                        |
| Reflection                             | 0 4 1 1 2 3 1 0                     |
| AI-generated summary                   | 11 4 1 0 1 0                        |
| Human-AI summary                       | 6 8 0 0 2 1 0                       |
| Explanation of summary                 | 7 5 5 3 1 0                         |

Table 1: Participants’ rating on whether Marvista provides extra value / requires extra effort in addition to reading an article.
4.4.6 Human-AI summary. Many participants liked how a human-AI summary further made the AI-generated summary "more personalized" (P3), "useful to reflect readers' interest" (P2), "caters to what the reader thinks" (P8 and P12), "allows a user to control the AI summary" (P17), and could incorporate each user’s desired focus (P13)—

When adding comment into consideration, I feel like the summary is more personalized for me." (P3)

Similar to their feedback on AI-generated summary, a subset of participants would use the human-AI summary to reflect on their reading of the article, e.g., using the dwelling time factor to reflect on where they had spent most time on (P3 and P4) or "to collect points that you read the most, but forgot to make a note of" (P11).

"Having the dwelling and highlighting feature was pretty useful for me to quickly understand what was mentioned in the whole article as I may have forgotten what was written after reading everything." (P9)

Participants also mentioned the possibility of influencing the human-AI summary during the reading process by intentionally highlighting or taking notes of contents that one would prefer being incorporated in the summary (P5, P6 and P14).

4.4.7 Explanation of summary. Participants provided diverse feedbacks on the value of summary explanations for addressing their curiosity (P3) and trust (P8) of the summarization model as well as contextualizing (P10) or deepening (P11) one’s understanding of the article.

Some participants used this feature as a bridge between the short summary to the recalling of more details in the article (P1 and P6) and to connect the summary to the "right sources in the article" (P2, P4, and P5).

"...useful if you don’t remember something mentioned in the summary, so you could go back to the source and reread what you missed." (P5)

Similar to and building upon the human-AI summary feature, we again saw the recurring theme of multiple participants (P4, P5, P6, P7, P9, P10, and P17) using explanations to reflect on one’s reading process, e.g., which paragraph one spent more time on (P7 and P10) or to review important paragraphs (P6 and P15) or those that one might have missed (P5 and P9).

A few participants preferred to use this feature more selectively, e.g., when "looking for verification" (P8) of the generated summary or only when one’s thoughts did not align with the generated summary (P12)—

"I think it’s valuable only when I want to go back and check if the summary is generated correctly according to what I want." (P13)

In terms of efforts, participants did notice the extra work of going back and forth between the summary and the explanations inserted into the original article (P5, P12, and P13). Quite a few participants almost missed this feature because it was not enabled by default and required a reader to check a box (Figure 6). Two participants (P2 and P5) suggested turning explanations on by default.

4.5 Summary of the Main Study

4.5.1 Reading behavior while using Marvista. Our findings in §4.3 mainly indicate how likely users would interact with each of Marvista’s features. Before reading, in over three quarters of the cases, participants made use of the filters. During reading, participants rarely opted out of the default focus mode but only scarcely used the active reading features (including AI-generated questions for reflection). After reading, in addition to the default AI-generated summary, in about two thirds of the time, a participant would generate a human-AI summary (with more emphases on dwelling time and highlight). In over half the time, participants would hover over the generated summary to see an explanation.

4.5.2 Recurring themes distilled from participants’ feedback on Marvista. Participants used Marvista not only to better understand the text they read but also to better understand how they read the text. Participants valued how the time and question filters could make reading more efficient, how focus mode could help a reader concentrate on the current paragraph, and how the summaries add to their understanding of the entire article. In the mean time, participants also reported using Marvista to better understand their own reading of the text, e.g., how they used the reflection tool to check their understanding of the paragraph. Even for the three after-reading features that were intended to help readers better understand the text, many participants still mentioned using those features to reflect on how they had read the article (e.g., to reflect where they had spent most time on). This suggests that summarization models can be beneficial and should be used for purposes beyond just summarizing text, just like how question generation can be beneficial for both planning what to read (e.g., question filter) and reflecting on how one has read certain text (e.g., reflection tool).

Participants found Marvista changed how they normally read. Many of Marvista’s features required participants to employ a quite different reading style than what they were used to, e.g., estimating how much time they want to spend before reading, reading one paragraph (only) at a time, pausing reading to answer reflective questions, and iteratively generating summaries after reading. The combination of all these features might significantly disrupt how people normally read. Indeed, participants’ feedbacks suggest that they were still trying to learn such a new process and we should expect their reading behavior with Marvista to evolve over time and the perceived value and effort to change accordingly.

Marvista’s different features are better fits for some reading scenarios but not for the others. Marvista is not a panacea for all reading scenarios. For example, participants considered the filters and generated summaries useful when reading to learn or acquire information but not when reading for entertainment, e.g.,
feeling pressured after setting a time limit. Similarly, reflecting on a paragraph was considered useful only when one intended to read the article thoroughly but not for a quick read to search for specific information.

One challenge is a lack of context, not the extra effort. Although participants noticed extra efforts in using several features, such efforts never seemed to have prevented their usage of Marvista. The challenge that often mattered seemed to be a lack of context, e.g., one challenge of the focus mode is trading off context for the focus of the current paragraph. Perhaps another more noticeable challenge is to understand an AI-generated question without context before reading or to understand isolated sentences AI extracts based on the filters. To mitigate this issue, one solution is to decrease the granularity, e.g., AI suggesting what paragraphs to read instead of sentences when using the time or question filter. Further, explanations could potential fill the gap of context, as demonstrated in the feature of summary explanations and reported by participants about how they used such explanations to connect the summary to contextual information in the article.

Instead of unconditionally trusting AI, multiple participants were able to identify issues with the model. Eight participants mentioned that they noticed a case where the model’s output (either a generated summary or question) seemed inaccurate, mainly because of including trivial details while missing what participants thought was important. Such awareness of AI’s issues also suggests that these participants likely compared AI’s output to their own thinking rather than unconditionally trusting AI even when AI might be wrong (a behavior called “over-reliance on AI” [5]). Over-reliance on tools like Marvista can also happen when users’ understanding of the article depends more on AI’s output than their own reading and thinking. Indeed, as pointed out by one participant, “[for] a developing reader it might make them lazy or dependent on it for finding the important parts of an article” (P8). To further look into possible over-reliance on Marvista, below we report a follow-up study.

5 FOLLOW-UP STUDY: OVER-RELIANCE ON MARVISTA

Following up on the main study, we are interested in investigating whether Marvista users might over-rely on the tool and understand the article based more on AI’s output than their own reading and thinking. As a proxy to probe and understand such over-relying behavior, we administered reading-related tasks and analyzed users’ task output as detailed below.

5.1 Tasks, Participants, & Procedure

The reading task was based on the same Pop Science website but now the materials consisted of three articles9 on the topic of diet. We asked participants to read each article, write a summary (two to three sentences long), and, after reading all three articles, write an overall personal review (three to six sentences long). We instructed the participants that a personal review differs from a summary in that it reflects what the reader thinks about an article. The lengths were merely recommendations without any min- or max-length enforcement so that participants could write about the reading materials with as few constraints as possible.

We employed a between-subject design with two conditions: we invited participants from the main study, of which five signed up for participation (Marvista Group). We then used mailing lists to recruit another five new participants who would be using the default website to read articles (Baseline Group). All 10 participants were engineering graduate students. All but one studied Electrical & Computer Engineering and the other was in Mechanical Engineering. All but one were aged 22-26 and the other was 33. The Baseline Group consisted of all male whereas the Marvista Group consisted of three female and two male.

Importantly, for Marvista users only, we modified the implementation of the tool so that participants must write their own summary before having access to the after-reading features. Once participants finished reading all three articles, they would write the personal review. They could choose to revisit any article as well as their highlights, notes, reflections, and summaries to help writing the review about the topic.

This study was IRB-approved and, similar to the main study, we went through the informed consent process before each session. We followed the same data collection protocol as the main study and briefed each participant what data would be collected. Each study session lasted for about an hour and each participant was compensated with a $25 Amazon gift card for their time.

5.2 Measurements

Our assumptions are: (i) For the summarization tasks, the more participants rely on Marvista, the more their summary will resemble the AI-generated summary. Even though Marvista users could not directly see the AI-generated summary before writing their own, their reading process is nonetheless supported by the AI’s summarization models (that enable, e.g., the time filter) as well as question generation models (e.g., question filter and reflection). (ii) For the personal review tasks, the more participants rely on Marvista, the more their reviews will resemble each other’s as Marvista might play the “common denominator” that attempts to unify their personal opinions about the articles.

Specifically, we measure the following with respect to each participant’s task output:

- Comparisons of a participant’s summary with both the AI-generated summary and human summaries written by three co-authors of this paper. We implemented the comparison using ROUGE score [23] and BERT score [12]. Specifically, when comparing a participant’s with the three co-authors’ summaries, we computed three scores and then took the average.

- The diversity of each participant group’s personal reviews, measured by pair-wise comparisons amongst each group’s personal reviews using both ROUGE and BERT scores, which indicate how one’s personal review is different from the others’ in the group.

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9Articles #1: https://www.popsci.com/does-the-hormone-diet-work/, #2: https://www.popsci.com/vegetarian-vegan-not-always-healthy/, and #3: https://www.popsci.com/high-fat-diets-make-mice-live-longer/.
5.3 Results & Findings

5.3.1 Are Marvista participants’ article summaries more similar to AI-generated summaries? As shown in Table 2, we conducted Mann-Whitney tests of the scores and found only one case (Article #2 using ROUGE score) with significant difference when comparing either group’s article summaries with the AI’s. None of the comparisons with human-written summaries found statistical significance.

5.3.2 Are Marvista participants’ personal reviews more similar to one another’s? We found a significant difference between Marvista and Baseline participants’ pair-wise within-group scores of their personal reviews. The average ROUGE scores were 0.28 for Marvista and 0.24 for Baseline (Mann-Whitney U : 24.0, p = 0.03); the average BERT scores were 0.12 for Marvista and 0.08 for Baseline (U : 27.0, p = 0.04). Such results indicate that Marvista participants’ personal reviews were more similar to each other. One key difference in the review writing process was that Marvista participants had access to the same AI-generated summaries for each article, which might have contributed to their higher degree of similarity with each other’s review. We tested this hypothesis by comparing each Marvista participant’s review with three AI-generated summaries concatenated as one piece. Overall, the mean ROUGE scores were 0.31 for Marvista and 0.26 for Baseline and the mean BERT scores were 0.07 for Marvista and 0.03 for Baseline. However, the differences were not statistically significant.

5.3.3 Did Marvista participants’ reading behavior change compared to the previous main study? We compared the log data of the five Marvista participants with that in the previous main study and found the following noticeable differences: (i) Both time and question filter usages dropped (time by 4% and question by 13%) while no-filter reading sessions increased from 24% to 36% of all the sessions, which was likely because participants preferred not to filter out text in order to write a comprehensive summary. (ii) When using the time filter, participants’ selected time increased from 53% to 79% of the estimated total reading time and, when using the question filter, the number of participants’ selected questions increased from 38% to 64% of all the generated questions, both of which could also be explained by their intention to read more driven by the two tasks. (iii) When not using any filter, participants spent much more time—16.4 minutes per 1000 words—than 5.2 minutes in the previous main study. Overall, it seems that participants more frequently chose and spent more time in no-filter reading sessions and, when they did use filters, they tended to ‘filter in’ more text both by time or by question.

5.4 Summary of the Follow-Up Study

We did not find statistical significance (except for one case) to support that Marvista participants’ article summaries were more similar to AI-generated summaries (nor less similar to human-written summaries). We did find Marvista participants’ personal reviews significantly more similar to one another than the Baseline users’. We hypothesize that seeing the AI-generated summaries might have contributed to such higher similarity within the Marvista group; however, we did not find statistical significance to support such a hypothesis. Given the mixed results and the lack of statistical significance, it remains inconclusive whether there exists over-reliance when interacting Marvista. Nevertheless, we believe our study tasks, design, and findings can serve as guidance for future work for further investigation into such behaviors.

6 LIMITATIONS, DISCUSSIONS, AND FUTURE WORK

6.1 Further Studies on and Designs to Address Over-reliance on Marvista

Building on the task, design, and preliminary results of our follow-up study, we plan to conduct further investigations with a larger number of participants on over-reliance when using Marvista. It is worth noting that Marvista’s current designs have already considered measures to discourage over-reliance, e.g., showing an AI-generated summary only after a user indicates finishing reading the article. When designing the output of the time and question filters, instead of letting a reader skip to AI’s recommend-to-read text, we chose to just highlight those text so that the reader still have equal access to all the text in the article. We believe this design choice reduces biasing readers with AI’s recommendations. We also believe that explanations of the summary can contribute to reducing over-reliance because it allows the reader to question the AI’s summary, e.g., by checking whether a sentence in the summary might have come from unimportant parts of the article.

Connecting to prior work, Bućinca et al. summarized three design strategies to mitigate AI over-reliance [5]: (i) asking the person to make a decision before seeing the AI’s recommendation, (ii) slowing down the process, and (iii) letting the person choose whether and when to see the AI recommendation. In the future, we plan to adopt these strategies in redesigning Marvista. For example, instead of showing the AI-generated summary right away, we can prompt the reader to first write their own summary (similar to what we did in the follow-up study) or answer a few global reflective questions.

6.2 From Supporting Reading to Encouraging Reading

According to the American Time Use Survey [11], there is a slow and continuous decline in how much time Americans spend on reading on a daily basis. In 2019, individuals between 15 and 44 read on average for 10 minutes or less per day. By involving AI to collaborate with and support human readers, Marvista intends to lower the barrier of reading (long) text and eventually to encourage people to read more. In our future work, we plan to deploy Marvista in a longitudinal study, to track how much each participant reads, and to investigate whether using Marvista leads to more reading. After that, we also would like to study whether people would still read more without using Marvista—whether Marvista can boost one’s intrinsic reading motivation or merely serve as an extrinsic assistive tool for reading more.

6.3 Technical Limitations of Marvista’s Current Implementation

6.3.1 Including more diverse participants. Currently our participants were all from a college-educated group who were familiar with digital devices and who often read for learning or research
we envision a large vocabulary of input gestures and modalities are employed a type of post hoc explanation [37] that compare the AI's summary with the sources (article text and user-generated summary). Current websites that host articles conventionally use `<p>` for a paragraph, although there could be some site-specific selection attributes (e.g., assigning article paragraphs a specific type of <id>) to differentiate between article paragraphs and other non-article `<p>` elements. Such rules can be easily book-kept in an external look-up file so that Marvista can support an extensible set of sites.

6.3.2 Supporting more websites. We only tested Marvista on the Popular Science website, although the tool can support other websites by modifying the rule in which it selects paragraphs of an article. Most websites that host articles conventionally use `<p>` for a paragraph, although there could be some site-specific selection attributes (e.g., assigning article paragraphs a specific type of <id>) to differentiate between article paragraphs and other non-article `<p>` elements. Such rules can be easily book-kept in an external look-up file so that Marvista can support an extensible set of sites.

6.3.3 A better measurement than dwelling time of each paragraph. Currently we use dwelling time on each paragraph to gauge a reader's interest of that paragraph, which inevitably includes non-reading time. A more accurate measure would involve using eye tracking mechanisms to calculate the amount of time a reader is actually looking at the text.

6.3.4 Exploring other types of summary explanations. Currently, we employ a type of post hoc explanation [37] that compare the AI's summary with the sources (article text and user-generated data). One limitation of this approach is that it cannot reveal the ‘black box’ process of how a summary is actually generated. To achieve a more comprehensive explanation, our future work will explore and incorporate other types of explanations, e.g., computing a saliency score of each paragraph (or even sentence) to reflect the actual process of how they are weightedly combined to formulate the summary.

6.3.5 Supporting other reading platforms. As shown in HCI literature (e.g., [31]), people read on a variety of platforms: phones, tablets, laptop screens, and desktop monitors. Smart phones, in particular, have become the dominant platform for accessing all kinds of information including reading articles [25]. We are interested in redesigning Marvista as a smart phone app. Specifically, we envision a large vocabulary of input gestures and modalities are possible in the focus mode beyond conventionally scrolling the text up and down. Further, the presentation of the text can go beyond the traditional format, e.g., as conversations between the reader and the AI where the two can ask and answer questions related to the text to enhance the interactivity of reading.

Table 2: Comparing participants’ summaries of each article with AI-generated and human-written summaries, showing the average (standard deviation) of ROUGE/BERT scores as well as results of Mann-Whitney tests.

| Article | ROUGE score | BERT score | ROUGE score | BERT score |
|---------|-------------|------------|-------------|------------|
|         | Marvista    | Baseline   | U           | p          |
| #1      | 0.31 (0.03) | 0.33 (0.05)| 10.00       | 0.34       |
| #2      | 0.34 (0.07) | 0.21 (0.06)| 2.00        | 0.02       |
| #3      | 0.25 (0.05) | 0.19 (0.07)| 10.00       | 0.34       |
|         | Marvista    | Baseline   | U           | p          |
| #1      | 0.37 (0.02) | 0.43 (0.05)| 6.00        | 0.11       |
| #2      | 0.24 (0.06) | 0.27 (0.01)| 6.00        | 0.11       |
| #3      | 0.31 (0.03) | 0.29 (0.05)| 10.00       | 0.34       |

6.3.6 Overcoming current limitations of NLP models. Currently, our NLP models generate two types of summarizations. Extractive summarization: Directly selecting a few text subset from a given document can be simplified as a sentence ranking problem. Before a user reads an article, Marvista highlights several sentences based on the time or question filter. However, as mentioned by several participants, at times it can be hard to understand an extracted sentence without reading its context and if a user needs to read more context to understand our recommended sentences, then the time saved while reading is limited. In the future, Marvista can involve coreference resolution model to detect and annotate ambiguous entities. For example, in Figure 1h, it will be more understandable as an extractive sentence if we replace the "they" in the paragraph "they found that patients infected with the Omicron..." to "The South African Medical Research Council found...".

Abstractive summarization: The abstractive summarization model used in Marvista is trained on the News articles because it has the richest human summary annotations. However, Marvista is a general tool that might be applied to any domain of text. There are two potential ways to mitigate this issue. The first is joint training with multi-domain summaries but it could be very costly to scale up. The other way is to conduct unsupervised reference-free pretraining such as masked-language modeling on the type of articles on which a reader focuses. Another major limitation of neural summarization models is the length of input and output that Marvista can digest. Existing generative language models has a fixed maximal number of input tokens such as 512 or 2048 tokens. Thus with extremely long articles Marvista can only take truncated article as input. In addition, the length of output summary and the granularity of the summary are highly depending on the training data annotation. For example, the summary annotated in XSUM [34] is shorter and more abstractive than the one annotated for the common CNN/Daily Mail corpus [33]. Lastly, the way Marvista incorporating user explicit...
or implicit feedback into summary generation could be one of the future study. In the current design, Marvista adjusts the encoder attention weights in a heuristic way without fine-tuning any model parameters.

**Question generation:** The existing generated questions might focus too much on low-level facts and do not capture the high-level ideas of the text. The primary reason is that the training QA corpora are mostly designed for the machine reading comprehension task, which usually contains short and factual answers. To generate more meaningful questions beyond remembering, our future work involves training models that produce questions at the level of understanding, applying, analyzing, evaluating, and creating.

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