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Priming at Scale: An Evaluation of Using AI to Generate Primes for Mobile Readers

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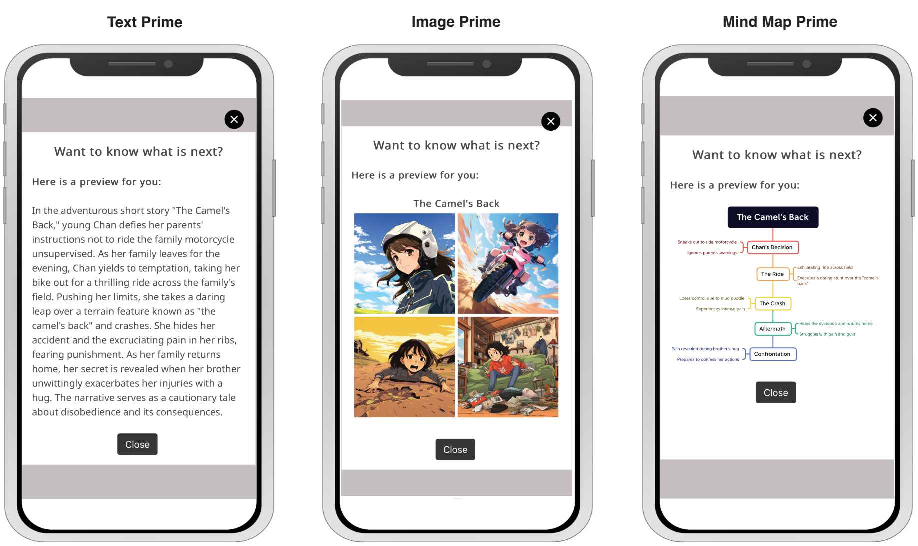

Figure 1: An example of the generated text, image, and mind map priming cues used in our study, shown on a mobile platform.

Abstract

Text summaries, images, and mind maps are well-known methods for priming readers to better engage with content. Previously, these

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"primes" needed to be hand-crafted, limiting their use. The advent of generative technologies makes the automatic creation of custom primes for any passage a realistic possibility. Here, we evaluate the efficacy of primes generated using AI on reading comprehension, reading speed, and re-engagement during mobile reading, which is notorious for its frequent interruptions. We used a mobile platform to present a reading task with an interruption to 44 readers (21 with English as a first language). We found that AI primes increased reading speed by an average of 7% for all readers in the initial reading task with no loss of comprehension and that visual primes had a significant interruption recovery effect for people whose first language was not English. Across all readers, text primes had both the initial reading speed increase and were overall most preferred.

CCS Concepts

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

Keywords

Reading interfaces, interruptions, mobile reading, generative AI, priming

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1 Introduction

Using "primes" such as text summaries, images, or mind maps has been shown to facilitate the cognitive processing of information (e.g., a text passage). These past studies used manually created primes, explicitly developed by experts for each reading passage to ensure they contained key information and effectively aided comprehension [14]. The time-consuming nature of designing these cues made applying them broadly across diverse content impractical. The advent of generative AI tools such as ChatGPT, Midjourney, and stable diffusion has made it possible to generate text, image, and mixed-mode content [40, 48]. Still, it is unclear if these generated primes can have the content quality and alignment necessary to positively impact reading performance. Additionally, we particularly focus on mobile reading performance as more text is increasingly consumed on mobile platforms where interruptions are omnipresent. We, therefore, study the impact of interruptions as a key challenge since mobile readers are subject to them by both real-world events and phone notifications while on the go. The aim is to generate insights that allow more efficient content consumption and effective recovery from interruptions for future reading technologies [19, 23, 27].

The theory of priming is that by showing a quick synopsis of the content, the reader gets in the right contextual "frame of mind" to take in the new material [59]. Priming cues can be of many different types, including: keywords, headings, image collages, mind maps, word clouds, highlighting, and text summaries; in past works, these have been investigated for their ability to guide attention and support learning outcomes particularly with respect to reading [14, 46, 57]. They have been shown to affect recall and memory processing tasks [46] and have been hypothesized to assist readers in overcoming the negative effects of reading interruptions [15, 19, 23, 27, 54].

With the spread of generative AI tools, priming cues can be created and contextualized in situ. In this study, we evaluate the effectiveness of three types of primes generated with the assistance of AI tools, so-called "AI-primes": text summaries, representative images, and mind maps. We use generative technologies to create these as detailed in subsection 3.2, but for this study, we used human-in-the-loop refinement. As these technologies improve, this process could eventually be fully automated. Our primary research questions are:

- **RQ1**: How do AI-assisted primes compare to each other with respect to reading speed, comprehension, and re-engagement after an interruption?
- **RQ2**: Which AI-assisted priming representation – textual, image, or mind map – are perceived as most effective?

In a user study with 44 participants, we evaluated the effectiveness of AI-primes by introducing a reading task with an interruption on a mobile platform. We measured reading speed and text comprehension before and after a planned interruption. We found that all types of AI-primes motivated faster reading speeds for the initial reading task (before the interruption), an average 7% increase over the "no prime" baseline, with text showing a slightly stronger effect. After the interruption, the effect of the primes was reduced, and the only impact on any group was the image prime for participants whose first language was not English. In terms of subjective ratings, both image priming and mind maps were perceived to pose less risk of spoiling the story, although text priming was the overall favorite. The text primes were perceived as most helpful and resulted in higher comprehension of inferential questions.

Our research is limited to assessing the impact of AI-primes on longer fictional passages read on the mobile platform, however, within this scope, we show these primes may have a positive impact on reading metrics and that specific types of primes may be better suited for different purposes and reader types.

2 Background and Related Work

Prior work shows that using different types of priming stimuli aids text navigation and reader engagement [14]. *Priming* is a way of facilitating the cognitive processing of a stimulus (e.g., a text passage) through prior exposure to concepts related to it [59]. An example of priming would be talking to someone about different kinds of fruit and then asking them to name something red. Because of the fruit "priming stimulus", a person is more likely to answer apple rather than firetruck [13, 44, 47]. Priming has been shown to help with memory encoding and retrieval [37, 50] and facilitate text comprehension [4] in normal reading scenarios and even while skimming [15, 51]. Our study explored three types of priming cues: textual summaries, visual summaries, and conceptual summaries in normal reading scenarios. While our three strategies integrate generative AI to offer a variety of information summarization methods, recent research primarily focuses on using generative AI to modify the difficulty or length of passages [7, 32, 53]. We describe our strategies and the related research in the following subsections.

In our study, we use three types of primes: text summaries, image summaries, and mind maps, which are a type of conceptual summary. Text summarization is a well-established task in natural language processing that takes long passages of text as input and attempts to provide a shortened, concise, and coherent summary of the passage as output[1, 2, 16, 29, 30, 38, 67]. In recent years, large language models such as GPT-3 [42] and GPT-4 [43] have made text summarization widely accessible. Users have shown strong preferences for these systems even if they sometimes lag in traditional automated metrics [28, 58]. Images offer an alternative to text summarization. Prior work has shown that illustrations constructed from the text can aid the learning process [10] and that enhanced thumbnails can help users find relevant pages more quickly than text summaries [64]. Early work in image generation from text looked at using image retrieval from text to identify existing images or image collages to compose [5, 68]. Still, recent advances in multi-modal generative AI can now create more complex and realistic images from a text prompt [48, 52, 65]. Mind maps [8] are conceptual summaries where concepts are represented as nodes with text, and edges are drawn to represent relationships between the concepts. Prior work has found that mind maps can assist learning and allow readers to recall information more effectively [12, 36]. Mind maps have also been found to improve reading comprehension for individuals learning English as a second language [33]. There has been relatively little work on automatically creating high-quality mind maps. Still, some prior work has studied semantic and dependency parsing to extract key concepts and their semantic relationships [17, 41, 69]. In this work, we explore using ChatGPT to create mind maps from passages of varying length and complexity. We describe our implementation of each type of priming stimuli in Subsection 3.2.

We use a mobile reading task to measure the impact of the primes on reading speed, comprehension, and re-engagement after interruption. Mobile reading is representative of how many documents are currently consumed. It is often subject to interruption, particularly when documents require more than a few minutes to read [31]. In multiple studies, interruption has been shown to decrease reading comprehension and the users' ability to re-engage with the original task [19, 23, 27]. Methods for addressing the negative impact of interruptions primarily include: minimizing or delaying interruption [18, 23, 24, 45], preparing users for interruption [22], and supporting task resumption after an interruption [25, 34, 54]. Our study uses an interruption that can be reasonably anticipated, and we hoped that being primed would enhance the reader's ability to return to the passage's context more easily. In summary, our study aimed at evaluating the effectiveness of three types of AI primes: textual, visual, and conceptual, using the established metrics of reading speed, comprehension, and re-engagement after interruption. We answer the call for future research to include diverse participants to advance the study of personalization in reading activities [39, 56, 61].

3 Experimental Design

To answer our research questions, we devised an experiment during which we exposed participants to different types of AI-primes and had them engage in a reading task that was systematically interrupted.

3.1 Reading Materials

We selected reading passages at the 8th-grade reading levels a level we deemed appropriately challenging without being overly difficult for our university-recruited participants, based on recommendations from recent readability research [6, 61]. Additionally, we chose fictional articles to ensure participants were not familiar with the content, reducing the likelihood of bias from prior knowledge. We selected five articles from the online easyCBM repository [3][1], which contains longer articles spanning approximately 1500-1700 words and which provides comprehension tests for the articles comprising 20 professionally crafted multiple-choice questions spanning three comprehension tiers: literal (7), inferential (7), and evaluative (6). The readability statistics of the selected five articles are included in the Appendix in Table 2 and Table 3.

3.2 AI-Assisted Priming Cues

We chose to investigate three different types of priming representations – text priming, image priming, and mind map priming – because each has unique characteristics that can influence reading comprehension in different ways. Unlike previous studies where priming cues were created manually, requiring significant human effort [14, 57], we used GenAI tools to generate all our primes. To ensure consistency and quality across the different priming types, we derived four key design criteria based on recommended guidelines in previous research [4, 14] to ensure consistency across different priming cues:

- **D1: Relevancy to the content**: Priming cues should closely align with the key themes, events, and ideas of the reading material.
- **D2: Consistent visual layout**: Consistency should be maintained across different priming cues, especially in image-based primes, where continuity of characters, settings, and scenes is important for maintaining reader immersion.
- **D3: Succinct and informative**: Primes should be designed to balance informativeness with brevity, offering enough information to support comprehension without overwhelming the reader.
- **D4: Mobile platform suitability**: All priming cues should be tailored for optimal readability and usability on mobile devices.

We designed the priming cues following the above design criteria using GenAI tools[2]. We experimented with tools such as OpenAI's ChatGPT[3] graphical interface (running the GPT-4 model, Mar 14,

[1] Sample articles and questions are provided in the supplementary materials
[2] The primes were generated between July 2023 and August 2023 using available GenAI tools
[3] https://chatgpt.com/

2023 version), Midjourney V5 [4] as well as brainstorming apps like Xmind[5]. The process is illustrated in Figure 2 and described below:

- **Text-Priming**: We used ChatGPT to generate concise text primes for each article. A standardized prompt asking for a summary of no more than 100 words (see Appendix C.1 for details) was used to ensure consistency. After generation, primes were manually reviewed for accuracy and relevance to the original content. The 100-word limit was chosen to fit the constraints of the mobile platform, optimizing readability and user experience.
- **Image-Priming**: We used ChatGPT to identify four key narrative moments, which were then converted into a comic-style image collage using Gen-AI tools. We experimented with different text-to-image generating AI tools, such as DALL-E 2's online and API versions, GPT-4 Plugin MixerBox, Adobe Firefly (2023 version), and Midjourney V5. Among them, only Midjourney could generate consistent story characters and scene depiction. The final images were crafted in a comic-style format, using Midjourney's 'seed' function to maintain continuity across images. A detailed exploration of different AI tools and image-generation challenges can be found in the Appendix C.2.
- **Mind map Priming**: The mind maps were generated using a combination of ChatGPT and XMind, following XMind's guidelines[6]. The process involved converting a Markdown format text into a visual mind map, then refining it to fit mobile screen limitations. The specific steps and prompt details can be found in the Appendix C.3.

3.3 Interruption Tasks

As priming cues have been hypothesized to reduce the negative effects of interruptions [19, 27], we evaluated our AI-assisted priming cues by including interruption tasks in our study. This task included three sub-tasks: a letter recall task, a math task, and a Tetris-like game task. All tasks are attention-intensive and necessitate a degree of effort, aligning with the control processes for reading interruptions described by Walczyk [60].

3.4 Reading Experiment Interface

We developed a mobile web application using HTML5 and JavaScript running on a Google Pixel 2XL (6.0 inches, 1440 x 2880 pixels) Android phone using the open-source work of Wallace et al. [61, 62]. Fonts were standardized across all text passages.

The experiment comprised a welcome screen, study overview, participant consent, 5 reading tasks, and a post-survey. Participants were unaware of the study's research questions and were instructed to read normally, not to read aloud, and not to press the back button or refresh the app. Each of the reading tasks included a priming cue related to the reading condition, the reading task, a 20 question multiple choice comprehension tests and a subjective survey. The subjective assessment used a 5 point Likert scale to assess the extent to which the prime was found to be helpful, distracting, "spoiling", enjoyable and helpful. After all reading tasks were completed, a post-hoc survey was used to gather information about participants' demographics (age, native language, other languages), reading experience (frequency, type of content, device of choice), and their reading ability (speed and comprehension) using 5-point Likert scales. We also asked participants to self-report any reading-related challenges: vision (normal, corrected), learning disabilities, or medical issues that might impact reading. Post-survey questions are provided in Appendix §B.

[4]https://www.midjourney.com/
[5]https://xmind.app/
[6]https://xmind.app/blog/chatgpt-and-xmind-how-to-create-a-mind-map-with-chatgpt/

3.5 Lab-based User Study

The study was approved by the [Anonymous] Ethics Committee (Project ID: [Anonymous]).

3.5.1 *Study design.*

We performed a within-subject laboratory-based user study where every participant read five articles under five different reading conditions:

- No-interruption + No-priming: A natural reading baseline
- No-priming: The reading task with the interruption but no prime.
- Text-priming: An AI text prime is shown at the beginning of the task and readers are interrupted.
- Image-priming: Identical to text priming but with an an AI image prime
- Mind map priming: Identical to text priming but with an an AI mind map prime

All the reading conditions were counterbalanced to avoid the order effects. The passage order was randomly shuffled. At the beginning of the study, we led participants through a "demo round" with a short passage (175 words), the interruption task and a short quiz (2 questions) to familiarize them with the study.

3.5.2 *Participants.*

We initially recruited 56 participants through a university notice board and mailing list. Five ($N = 5$) were excluded because they could not complete the study due to a technical issue. Two ($N = 2$) were excluded due to self-identification as having a reading-related disability in the post hoc survey, and ($N = 5$) were excluded due to outlier scores for either reading speed or comprehension using the interquartile range method. All the participants were compensated for their time and contribution by e-gift vouchers. In total, we analyzed data from 44 participants (34 female, 9 male, and 1 non-binary) where 21 participants belonged to 18-24 age group, 18 participants to 25-34 age group, and the remaining 5 participants were above 35 years old (M = 25.57 years, SD = 7.90 across all each groups). Of these, 19 participants identified themselves as having English as their first language, 22 as English Proficient, and 3 as English Competent.

4 Analysis and Results

We present quantitative and qualitative results for our research questions. Our quantitative evaluation metrics include: **reading speed** of the text passages measured in words per minute (WPM), the **comprehension score** for the 20 multiple choice questions per passage, the time spent on the quiz (**comprehension time**) and the **time viewing** the primes. Our qualitative metrics included evaluating the extent to which the primes were seen as **helpful**, **distracting**, a "spoiler" for the story **spoiling**, **enjoyable**, and

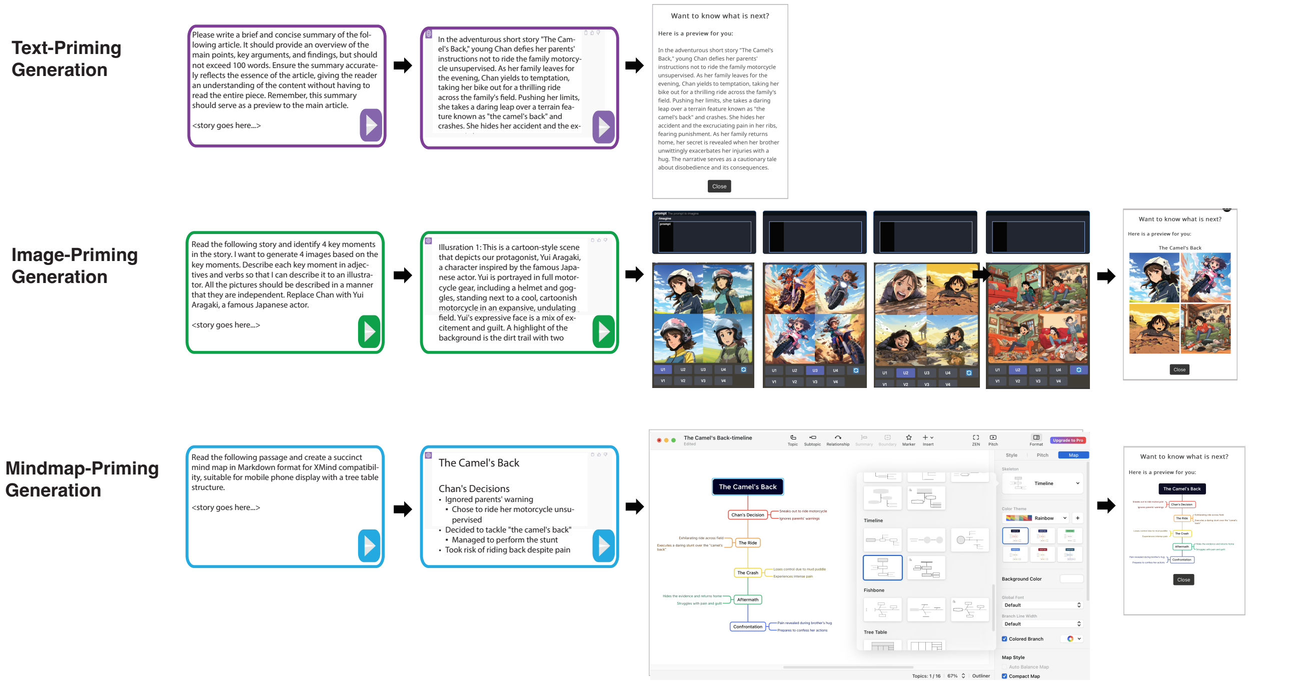

Figure 2: A figure showing how text-priming, image-priming, and mind map priming cues were generated using Gen-AI tools.

the extent to which they believed it helped them **remember** the content.

4.1 Objective Metrics to Answer RQ1

We evaluated the differences in comprehension scores, comprehension time, and reading speed for the participants in no-priming condition with *text*, *image*, and *mind map* reading condition using a linear mixed-effects model (LME).

To answer RQ1, we designed separate LMEs to compare the effects of individual predictors, similar to related readability research [61]. We held each of the reading conditions – *text*, *image*, and *mind map* – as fixed effects, and participant ID and passage ID as crossed random effects in our model. Since previous research has shown that individual differences, age, and native language influence reading [11, 55, 56, 61], we tested the influence of these factors by adding them to the LME model. We applied post-hoc Tukey's Honestly Significant Difference (HSD) test to compare the differences.

Our quantitative analysis yielded three significant results:

(1) Participants in all the priming conditions read faster compared to no-priming condition ($Speed - up_{Text\text{-}Priming} = 22WPM, p < 0.05$, $Speed - up_{Image\text{-}Priming} = 19WPM, p < 0.05$, $Speed - up_{Mindmap\text{-}Priming} = 34WPM, p < 0.001$).
(2) For people who did not have English as a first language, *Image-Priming* significantly positively impacted reading speed after the interruption with a reading speed improvement of 8.3% ($p < 0.05$).
(3) Participants scored 8.0% higher on inferential questions when viewing *Text-Priming* compared to *Mindmap-Priming* ($p = 0.05$).

The average reading times per priming cue were: text (35.7s), image (16.7s), and mind map (28.5s). For people with English as a first language, they read 33.4% faster in text prime reading (28.3s) compared to those who learned English later (42.5s). This increase proved statistically significant ($p < 0.05$).

4.2 Subjective Metrics to Answer RQ2

To answer RQ2 and evaluate which priming cues readers perceived as most effective, we analyzed participants' subjective ratings for the variables helpful, distracting, spoiling, enjoyable, and remembering using a non-parametric Friedman test. We compared each AI prime, text, image, and mind map, to the no priming baseline. If significant differences were detected, pairwise comparisons were conducted using the Wilcoxon signed-rank test, with Bonferroni correction applied to control for multiple comparisons.

Our analysis revealed a significant difference between text and both image and mind map priming for "helpfulness". Post-hoc analysis revealed a significant difference in perceived spoiler characteristics between text and image priming (Z = -2.18, p < 0.05) but did not yield a significant difference in text and mind map priming (Z = -0.61, p = 0.54). Post-hoc analysis also did not yield a significant difference in perceived enjoyable characteristics between text and image priming (Z = -1.28, p = 0.20) or between text and mind map priming (Z = -1.90, p = 0.06). Table 1 shows our results with only the variables that retained significance in post-hoc analysis highlighted in bold.

Table 1: A summary of participant's subjective ratings for all the priming cues in terms of different subjective metrics.

	Text		Image		Mind Map		Comparison		
	M	SD	M	SD	M	SD	$\chi^2(2)$	p	Kendall's W
Helpful	**4.05**	0.959	**3.28**	1.12	**3.28**	1.39	13.77	**0.001**	0.156
Distracting	2.17	1.13	2.33	1.06	2.44	1.30	0.59	0.74	0.007
Spoiler	**2.98**	1.27	**2.26**	1.14	2.60	1.16	10.75	**0.004**	0.122
Enjoyable	3.92	1.10	3.53	1.03	3.23	1.36	10.38	0.006	0.118
Remember	4.00	1.15	3.44	1.26	3.35	1.34	7.65	0.022	0.118

4.3 Qualitative Analysis: User's Response about Three AI-Assisted Priming Cues

To develop a more thorough comprehension of user sentiments regarding the three priming cues (RQ2), we conducted a thematic analysis of participants' responses concerning their favorite and least favored summaries. The **most people chose text prime as their favorite 45.5% (N=20)** of whom 12 had English as a first language. The text prime was praised for its *clarity* (N=8), *effortlessness* (N=7), *thoroughness* (N=6) and *familiarity* (N=2). Seven participants chose text as their least favorite, only two of whom had English as a first language. The most common criticism was *verbosity*, requiring extra time for comprehension. One participant mentioned that the text prime made them focus on it rather than the story itself, causing them to skip story details. The image prime was chosen as a favorite by 27.3% (N=12) of participants selected the image prime as their favourite, 4 with English as a first language. Participants preferred it primarily for its ability to stimulate *imagination* (N=4) and improve *memorability* (N=3). Of the 17 that chose image as their least favorite (8 English as first language) the most common criticism were its *ambiguity* (N=7) and its *limitedness* (N=8). The participants found the image prime deficient in details and unhelpful in grasping the future textual content. The mind map prime was selected as the favorite by 27.3% (N=12) of participants, with 5 participants having English as their first language. Overall, participants reported that it made complex information more accessible and organized. Four specifically praised its *informativeness*. One participant mentioned that the different shapes, colors, and lines aided understanding. Of the nineteen that selected mind map as their least favorite (11 with English as a first language), Most of them expressed the property of *distractedness* (N=5) and *complication* (N=5) regarding the mind map prime. Three participants believed it hindered memorization, and two participants disliked its *formalness* for narrative text.

5 Discussion and Limitations

Our participants were native and non-native English speakers (Non-ES), answering the call for future research to diversify participants to study readability for all [39, 56, 61]. However, our efforts were limited to evaluating the efficacy of AI generated primes for English text at the 8th grade level on a mobile platform in a controlled laboratory setting. We found that readers anticipated and relied on our AI generated primes, improving pre-interruption reading speed. This aligns with the Zeigarnik effect, which suggests that interruptions enhance task memory [66], and prior research showing improved task performance after interruptions [35]. Thus, our work shows initial evidence of AI generated primes to help prepare users for interruption[22] and support task resumption after an interruption [25, 34, 54]. One explanation for our results on the relationship between priming and reading speed is that priming allows readers to engage in skimming reading behaviors [15]. For example, recent research shows that an AI-resilient text rendering technique for reading and skimming documents improved readers' choices on what text to skip when skimming [21]. Our results show promise that image summarization as primes can yield similar benefits to a Grammar-Preserving Text Saliency Modulation (GP-TSM) [20]. The common thread among our research is preparing and helping readers to recover their reading efforts while retaining comprehension. This is especially challenging across cultures [51]. Future work should study diverse methods and styles of prime generation across diverse content, such as business reports or infographics.

Our findings suggest people want AI tools that can seamlessly integrate into reading to assist during interruptions. All participants preferred using primes while reading, thus providing evidence that future reading systems should use Generative AI to integrate personalized primes across cultures. However, mirroring prior work, participant preference in primes did not predict effectiveness [63]. Pointing towards the call for personalization [61], we found that individual differences played a significant role in reading speed, comprehension, and cue effectiveness. Participants with English as their first language processed primes faster, while those who learned English later benefited more from image summaries. Images significantly increased reading speed for Non-ES readers, offering quicker processing than text primes with equivalent benefits. This result builds on prior research studying mind maps [14] and mirroring results showing the benefits of priming for EFL readers learning English in a foreign country [26]. While reusable image summaries across languages may reduce equity gaps in readability, addressing limitations from recent studies [9, 39]. These results align with recent studies showing AI generated content improves comprehension [26, 49]. Our findings suggest a promising future for assistive reading technologies, with AI providing targeted, adaptable support for diverse readers in common scenarios.

6 Conclusion

Priming has proven to be an effective way to improve reading in terms of speed and comprehension but generating primes for individual texts is a labour-intensive task [10]. By using generative AI to produce primes, we can overcome this major pain point. Our results show the feasibility of AI-primes, especially text and images being good enough and relevant enough to the text they represent that users prefer them to no prime (45.5% preferring text-priming, 27.3% each preferring image-priming and mind map-priming, and none of them selecting "None of them" option). We found that all generated primes increase initial reading speed (8%) and that image primes help readers whose first language is not English re-engage with reading faster after an interruption. Although the best prime for any text is likely to be text and reader-dependent, the power of generative AI allows any prime to be generated for any reader as soon as they open a document. As reading becomes more mobile and interrupted, we believe that cognitive aids like text, image and mind map primes will help people engage more effectively with content and that AI will make it possible to generate this assistance tailored to every reader for every text.

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A Readability Statistics of Selected Articles

The readability statistics of selected articles are shown in Table 2 and Table 3.

B Post-Survey Questions

Below are copies of the post-survey questions. Questions marked with a * are required.

(1) What is your age? (in years) * Short answer text
(2) What is your gender? *
  - Male
  - Female
  - Non-binary
  - Prefer not to say
(3) What is/are your native language(s) *
  - English
  - Other:
(4) What other languages do you speak? Long answer text. Leave blank if you only speak English.
(5) Please describe your current occupation: * Long answer text.
(6) How often do you use mobile reading applications or e-books? *
  - Several times a day
  - Once a day
  - Several times a week
  - Once a week
  - Rarely
(7) Do you feel comfortable with reading articles written in English?
  - Not comfortable
  - Somewhat comfortable
  - Very comfortable
(8) How would you rate your speed as a reader? * Likert Scale 1 (Very Slow) – 5 (Very Fast)

Table 2: Readability statistics of selected articles including the common scores: Flesch Kincaid (FK), Gunning Fog (GF), Simple Measure of Gobbledygook (SMOG), Coleman Liau (CL), and Automated Readability (AR).

Article	FK Reading Ease	FK Grade Level	GF Score	SMOG Index	CL Index	AR Index
1	76.4	6.3	8.6	6.7	9.5	6.2
2	76.8	7.5	10.2	6.3	9	8.5
3	68.5	7.4	10	7.5	11	7.4
4	77.8	5.6	7.9	5.9	9.5	5.2
5	83.1	5.8	8.4	5.2	8.3	6.2

Table 3: Text statistics of our selected articles where *Sent* stands for "Sentences".

Article	Sent.	Words	Complex Words	Complex Words %	Words per Sent.	Syllables per Word
1	131	1943	169	8.70%	14.83	1.36
2	79	1584	88	5.56%	20.05	1.30
3	99	1461	160	10.95%	14.76	1.46
4	138	1749	132	7.55%	12.67	1.37
5	96	1611	69	4.28%	16.78	1.26

(9) How would you rate your reading comprehension? * Likert Scale 1 (Very Poor) – 5 (Excellent)
(10) Have you ever been diagnosed with a reading or learning disability (e.g., dyslexia)? If yes, which one and how long ago?
(11) Do you have normal or corrected vision? *
- No
- Yes

(12) Which summary did you like the most? *
- Option 1: Text summary
- Option 2: Image summary
- Option 3: Mindmap summary
- None of them

(13) Please describe your reasons, what did you particularly like about your favourite summary? * Long answer text.
(14) Which summary did you like the least? *
- Option 1: Text summary
- Option 2: Image summary
- Option 3: Mindmap summary
- None of them

(15) Please describe your reasons, what did you particularly dislike about your least favourite summary? * Long answer text.
(16) Do you wish to participate in our future studies
- Yes
- No
- Maybe

(17) Do you have any additional comments about the summaries or the conducted study? Long answer text.

C Detailed Priming Generation steps

C.1 Text Priming

For each article in our reading list, we employed ChatGPT to generate concise text summaries. We standardized this process by using the same prompt for all articles, which reads: "Please write a brief and concise summary of the following article. It should provide an overview of the main points, key arguments, and findings but should not exceed 100 words. Ensure the summary accurately reflects the essence of the article, giving the reader an understanding of the content without having to read the entire piece. Remember, this summary should serve as a preview of the main article." After generating these summaries, we manually reviewed them for accuracy to ensure they faithfully represented the original articles. The 100-word limit for each summary was chosen based on the average number of words that could be displayed on a single page within our application, optimizing the user experience.

C.2 Image Priming

For each article in our reading list, we initially prompted ChatGPT with the task to 'identify four crucial moments from the narrative, elaborating on them with adjectives and verbs to effectively communicate the scene to an illustrator.' We then experimented with various image-generating AI tools, including DALL-E 2's online and API versions, GPT-4 Plugin MixerBox, Adobe Firefly, and Midjourney. Among these, only Midjourney offered the unique capability of consistently producing characters across the story's four core images using their 'seed' function.

Regarding our experimentation with image generation, we initially tried converting text summaries directly to images using various image-generating tools, but this approach yielded inconsistent or irrelevant images. We also attempted to divide the text summary into four chunks using ChatGPT and then pass these to image-generating tools, but this too, did not yield satisfactory results. Another approach involved dividing the text summary into four separate moments, each described with adjectives and verbs, to communicate the scenes to an illustrator. While this worked somewhat, the images generated were inconsistent, particularly regarding character representation. We then tried generating consistent images by creating characters' faces based on famous personalities but found the images too realistic and unsuitable for storybooks. Finally, we succeeded by explicitly instructing the image-generating apps to produce images in 'comic-style' or 'cartoon-based' formats and utilizing the 'seed' function in Midjourney to maintain background consistency. This approach yielded the desired results.

C.3 Mind map Priming

For the mind map summary, we adhered to the guidelines outlined on XMind Blog. The process was divided into four steps. In Step 1, we prepared a clear prompt for ChatGPT, asking it to generate text in Markdown format that could be converted into a mind map using XMind software. For Step 2, we utilized cloud-based software to convert the generated text into Markdown format. In Step 3, we imported this Markdown text into XMind software to create the initial mind map. Finally, in Step 4, we refined the generated mind map as it was too large for our mobile application's screen. This refinement was achieved by revising the initial prompt and repeating the entire process.