“Good to Know, but Not a Good Time to Read”: Investigating Opportune Moments for Pushed News Reading

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Pushed notifications from mobile news apps are an important means of access to news, but people do not always have sufficient time or cognitive resources to process them. Nevertheless, whether and to what extent news-reading behavior and performance are associated with particular moments of pushed-news delivery are understudied. We therefore built NewsMoment, a smartphone news-aggregation app that logs its users' reading behavior and sends pushed news notifications for real news items from up to nine news organizations. Our ESM study found that pushed news was associated with two shallow reading modes – Scanning and Unengaged – which, though seemingly similar, were distinct in their prevalence, triggers, opportune moments, and self-assessed reading engagement and news items' perceived credibility. We also found that opportune moments for reading entire articles were distinct from those for receiving notifications and checking news titles. These findings inform our pushed-news design recommendations aimed at reducing shallow reading.

CCS Concepts: • **Human-centered computing → Empirical studies in ubiquitous and mobile computing**.

Additional Key Words and Phrases: Mobile notifications; mobile receptivity; opportune moment; interruptibility; ESM

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1 INTRODUCTION

As mobile devices and mobile Internet become ever more pervasive, people's relationship to news is becoming portable [83]. Users of such devices and services can now consume news content anywhere, at any time, and in various forms [17, 96, 102]. Numerous studies have shown that news consumption has gradually shifted from desktop to mobile devices [1, 67, 69, 87], not only because it is convenient to access news on the latter, but also because smartphone interfaces make the process of accessing and sharing news easier [87]. Recent reports have indicated that more people now consume news on phones than on desktop computers [67]. As well as having emerged as a mainstream channel for accessing news, smartphone news applications allow their users not only to “pull” news from them, but also to receive “pushed” news notifications [26], which increases their volume of news consumption, as compared to those who disable push notifications [88]. Because of this volume effect, news organizations increasingly tend to make use of push notifications [104]. However, this trend means that news-app users are receiving an increasing overall quantity of notifications, which are essentially interruptive and distracting [10, 60, 68], especially when they are sent at inopportune moments [62, 79, 81]. Although short-form reading, including news reading, often takes place in short interludes between, or even within, other activities [19], this does not necessarily mean that users will be receptive to pushed news at any time. In particular, smartphone users' available cognitive, attentional, and time resources for reading news articles fluctuate throughout the day and from one activity to another [21]. And, when they are multitasking or their attention is otherwise divided, their news-reading performance (i.e., comprehension and counter-arguing) can be also lower [38, 45]. However, unlike with other types of reading that are more personal, inattentive/low-performance reading of news can have a negative social impact. That is, research has shown that incomplete and shallow processing of news is one of the major factors contributing to misinformation dissemination [64], because the sharer may not know or suspect that the news they are sharing is fake [23]; sharing news items is also found to often follow shallow reading [39, 72], including sharing right after the readers stumble upon news [72]. For this reason, it is societally important to identify moments for the delivery of pushed news that will lead to thorough, deep reading of the associated news stories.

A growing body of literature is devoted to identifying opportune moments for delivering various types of notifications [12, 13, 21, 31, 46, 46, 49, 81, 85, 97, 101]. However, to the best of our knowledge, no previous study has investigated opportune moments for delivering pushed news to achieve deep reading of news articles. Our aim is to fill that research gap, guided by the following questions:

- RQ1: What are the common modes of news reading on smartphones, and how pervasive is shallow reading, particularly of pushed news?
- RQ2: How do smartphone users who have adopted a shallow news-reading mode assess a) their own news-reading performance, and b) the credibility of the news they are reading?
- RQ3: How does the perceived opportuneness of the moment for pushed-news notification delivery affect the likelihood that shallow reading will ensue?
- RQ4: In what activity context would users be more likely to a shallow reading mode?

To answer these research questions, we adopted a mixed-methods approach. We developed an Android news app called NewsMoment that aggregates news from nine popular news apps and delivers pushed news notifications. The app logs its users' reading behavior and phone-sensor data, and delivers experience-sampling method (ESM) questionnaires to capture users' contextual information about specific instances of news reading and self-assessment of their reading engagement, comprehension, and perceptions of the news items they read, and perceptions of the opportuneness of particular moments for reading the news. We invited 29 people to use NewsMoment for 14 days and observe their experiences and behaviors.

This paper makes four crucial contributions:

- It identifies four distinct modes of reading news items on smartphone news apps, and shows that the two shallowest ones are more likely to be triggered by pushed news notifications than by self-initiated reading.
- It establishes that these two shallow reading modes are distinct from each other, not only in their prevalence and objective reading patterns, but also in their triggers, opportune moments, associated news categories, and very possibly self-rated reading engagement and news items' perceived credibility.
- It shows that opportune moments for reading entire news articles are distinct from opportune moments both for reading notifications and for checking news titles.
- It highlights opportunities for future pushed-news services to increase the likelihood of deep reading.

2 RELATED WORK

2.1 Mobile News Consumption

And as long ago as 2018, the percentage of Americans who obtained news from a mobile device had reached 88% [25]. In short, people no longer consume news at fixed times or in fixed places, but can read it more actively and flexibly [16, 103, 105]. Moreover, outlets that offer mobile news seem to be progressively occupying more of readers' otherwise-unallocated time [7]; and spatially, news consumption's transformation from desktop-based to mobile also implies a greater variety of contexts in which news reading will occur, making it more likely to be subject to environmental factors [6]. It has been reported that mobile-news readers' engagement levels [70] and psychological factors (e.g., negative experiences) [53] influence their news-related behaviors and satisfaction. Nam et al. [66] also showed that leisurely reading can lead to very different reading behaviors, because readers select the material themselves and may not have any particular reading goals in mind, at least initially. Reading news while multitasking also negatively affects people's comprehension and ability to make counter-arguments [38, 55].

Given that reading on mobile devices differs fundamentally from reading on a desktop (e.g., due to the former's smaller screen size and unique interaction methods) [99], a growing body of literature is focused on patterns of news reading on mobile devices. Some of these studies have used self-report methods to explore mobile users' reading behavior [15, 58, 63]. For example, Molyneux [63] conducted two online surveys to measure news consumption across platforms, and found that – as compared to reading news on other devices such as computers and tablets – mobile news reading is shorter, more frequent, and spread more widely across the hours of the day. The locations of news consumption have also been captured through self-report methods [15, 96]. Van Damme et al. [96] collected personal diaries and conducted face-to-face interviews and reported that the majority of news consumption on mobile devices took place at home, either in the morning or the evening.

However, studies of such topics that rely on self-reported data may not precisely represent actual usage [5, 9, 14]. For example, Boase and Ling [5] examined the validity of self-report data by comparing it against server log data, and found that the former was of low criterion validity. Moreover, people's self-reports tend to overstate the frequency of their mobile-device use [41, 63]. To obtain a more detailed and reliable account of news-reading behaviors on mobile devices, some researchers have used logs to record them. For example, Nam et al. [66] found that touch-location data was useful in distinguishing a user's level of familiarity with a topic, while reading-time and scrolling data could be used to differentiate between reading content contextually or literally. Similarly, Homma et al. [33] used log data to identify a positive correlation between short dwell time in news articles and low user interest; and Grinberg [29] showed that article dwell time was the single best predictor of reading engagement. Carreira et al. [8] logged users' news-article reading behaviors and showed that it was feasible to recommend content based on such behaviors. Similarly, Constantinides et al. [15] logged their participants' interactions with a mobile news app, and demonstrated that logs could be used to build classifiers that recognized reader types. Different reading patterns can also lead to variation in reading performance. Li et al. [51], for example, showed that scrolling was associated with better memory of short texts, and lower mental and temporal demands, but greater visual fatigue.

Finally, Lagun and Lalmas [44] captured how much time people spent on different parts of news articles on websites (i.e., the header, body, and comments section) during a single reading session; then, they used k-means clustering with reading patterns to identify four engagement levels: bounce, shallow engagement, deep engagement, and complete engagement, from which different news-reading modes could be inferred. Another related study [29] clustered reading patterns and found some similar reading patterns to those previously identified by [44]: i.e., read (long), which was much like complete reading, and shallow reading. However, the latter was defined as less than 2% of the page having been viewed, quite different from the less-than-50% standard for shallow engagement [44]. Notably, the reading-behavior data used by both these studies were cross-platform.

In this paper, we not only identified four reading modes, which is similar to these works, but uncover how two shallow reading modes are distinct from each other in other characteristics, not merely observable reading patterns. And this would not have been possible without the integration of log data and in-situ self-report captured via ESM.

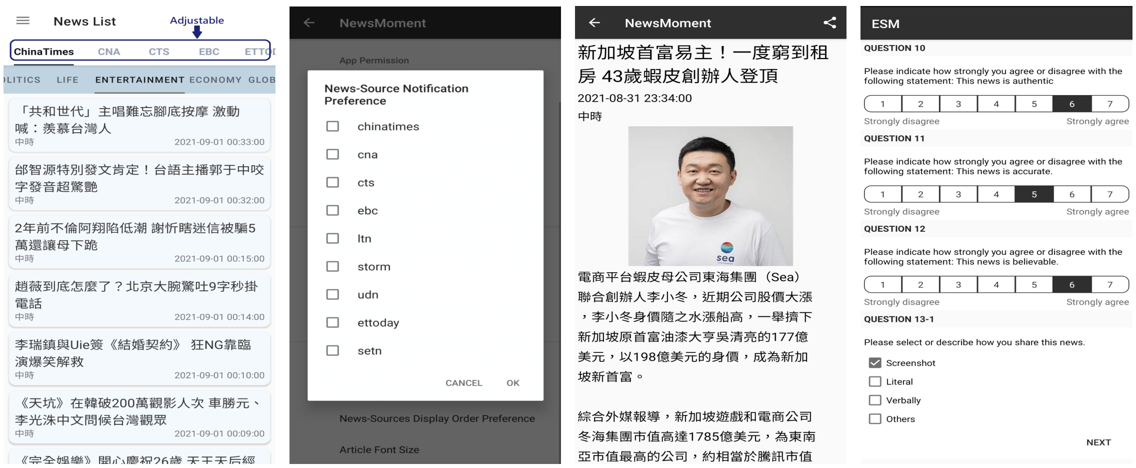
2.2 Opportune Moments for Delivering Content

Interruptibility research has been carried on for decades, with the wider aim of reducing interruptions in workplaces [71, 108] and desktop environments [18, 34, 37]. In recent years, considerable research attention has shifted to mobile receptivity [13, 32, 56, 59, 92, 107]. In particular, opportuneness describes whether a given moment is suitable for a person to perform a particular action [80]. Various other terms for and sub-types of opportune moments have been proposed, including interruptible moments [13, 32, 56, 59, 92, 107], break-points [2, 13, 27, 36, 73–75, 77, 79, 86, 89], transitions [91], receptive moments [28, 61, 93], and moments when users would be attentive [20] or responsive [47]. However, all of this research shares the aim of identifying, characterizing, and predicting good moments for people to receive notifications [81, 82, 94], including but not limited to messaging notifications [80] and ads [81, 101]. Research that explores moments for smartphone delivery of other pushed content that requires more engagement than notifications do is also growing, and so far has looked at questionnaires [47, 81], behavioral interventions [46, 49, 85], mini games [81], and learning materials [22], among other such content. However, different types of pushed content entail different types of actions, and thus, opportune moments for receipt of one type of it may not be applicable to other types [81]. Recent research on opportune moments for crowdsourcing tasks, for instance, suggests that different moments are perceived by users as suitable for different types of micro-tasks [13].

Thus far, however, we have little knowledge of opportune moments for reading pushed news. Okoshi et al. [76] conducted one of the few studies to date aimed at detecting interruptible moments for pushed-news delivery. Adopting Yahoo, one of the most popular news apps in Japan, as their experimental material, they used mobile sensing and machine-learning techniques to detect users' breakpoints, and then sent out news notifications during them. Okoshi et al.'s detection approach achieved success, leading to a 60% increase in click rate, but they did not measure whether their participants' engagement with what they were reading was careful/deep or surface/shallow [76]. Moreover, we will show later, people are likely to have different reading modes on pushed news notifications at different moments. We also provide evidence that the opportune moment for deep-reading of pushed news is distinct from the opportune moments for receiving news notifications and for checking news titles, respectively. All of these results are absent in the body of literature, and are offered in this paper.

3 METHODOLOGY

Both the quantitative and qualitative aspects of this mixed-methods study relied on our Android news app, NewsMoment, which allowed the participants to read news; logged their reading behavior and phone-sensor data; and delivered ESM questionnaires aimed at capturing specific news-reading instances' contexts, along with their subjective experiences of such instances, including self-assessment of reading outcomes and the perceived opportuneness of reading a piece of news at a particular moment. Further details are provided below.



(a) News List (b) Notification Preference (c) News Article (d) ESM Questionnaire

Fig. 1. Our news app’s (a) main page with news-source bar and category bar, (b) news-source notification preference, (c) news-article presentation with title, publication time, source, image, and content, and (d) ESM questionnaire displaying questions related to perceived credibility of news

3.1 NewsMoment

NewsMoment aggregates news from nine popular news apps in Taiwan and delivers news notifications. To capture participants’ news-reading behaviors and experiences as fully as possible, without skewing those behaviors or experiences, our design goal was for NewsMoment to closely replicate the participants’ usual news apps, including their user interfaces (UIs) and their patterns of pushed-news notification delivery.

3.1.1 Core Features and User Interface. NewsMoment’s UI is presented in Fig. 1. We compared the most popular news apps in Taiwan and identified their common design features. The design of NewsMoment’s UI was based on these features so that it would look familiar to most of our participants. As shown in Fig. 1a, our UI included a nested tab bar. The top tab bar is the news sources bar, which contains a list of the nine selected news sources that the app aggregates news from. NewsMoment users can determine which of these nine sources they want to receive news and news-related push notifications from Fig. 1b.

The tab bar second from the top is the news classification bar. The list of news-classification tabs that appears under each news source is identical to that organization’s own such lists. Again, the purpose of this was to maximize the perceived similarity between reading news in NewsMoment and reading the same news on authentic news apps. News content was crawled from the website of each news organization every 10 minutes, and included images, text, and ad text; all of this was then displayed in NewsMoment as seen in Fig. 1c. Also, it illustrates how the user is directed to the app’s built-in sharing function, whereby Android for users can share the news they have read via various other apps, e.g., Facebook, LINE, and Messenger.

3.1.2 Pushed News Notifications. To ensure that all the pushed news notifications the participants received were from NewsMoment, such that they would not be disturbed by receiving multiple notifications about the same news item, pushed news notifications from users’ existing news apps were suppressed. Thus, an important mission when designing

NewsMoment was to ensure that it created sets of pushed news notifications that were identical to those produced by each of its users' existing news apps, such that no-one would feel s/he had missed any such notifications due to having installed NewsMoment on their phone during the study. To achieve this, the research team installed all nine of the selected news apps on two experimental smartphones and collected their pushed news notifications. Once the NewsMoment on these phones detected such notifications, it collected their linked news items' titles and source names, and used those pieces of information to query news articles from our research server that stored crawled news, as discussed above. The server then compared the notification's title against news titles using Gestalt pattern matching [84] and found the most similar one using a similarity score. The news item that received the highest similarity score (which should be at least 0.5) was pushed to the participants' smartphones.

3.1.3 Data Collection. NewsMoment logs its users' news-browsing and news-reading behaviors. Specifically, it tracks the position of the user's *viewport* in the news, inspired by prior analytical work [43, 44]. First, each line of a news item's text (including its title, source, published time and context) and each image in it is defined as a block/unit, and NewsMoment records which blocks/units are visible on the screen per 0.1 second period. The app also logs users' actions such as scrolling, entry and exit, and use of the Android built-in sharing function. These logs allowed us to track what area within a news item each of our participants was focused on at any given time, from which we were able to generate advanced metrics such as dwell time of each viewport, scrolling speed (changes in viewports per second), and variances in scrolling speed. In addition, NewsMoment logged our participants' actions during article reading, including detailed of scroll gesture; whether the article was accessed through notifications or not, and shared or not; total dwell time. Finally, NewsMoment collected sensor data that might later help us identify opportunities in the future, as in previous work (e.g. [81]).

3.2 ESM Study

To capture participants' experiences of specific news-reading instances, and the contexts of those instances, including their self-assessment of their news-reading outcomes and perceptions of the opportuneness of the moments when news was read, we conducted an ESM study via NewsMoment, as described below.

3.2.1 ESM Mechanism. After participants installed our research app, they configured it, first by choosing a 12-hour (or longer) window of each calendar day during which they were happy to receive ESM questionnaires. NewsMoment then determined each participant's ESM-prompt schedule for the entire study period. ESM prompts were sent randomly at intervals of at least one hour, and the maximum number of questionnaires per day was set at 12 even if an individual's chosen window was longer than 12 hours. To minimize inaccurate self-reporting caused by recall bias, an ESM prompt was dismissed if not engaged with within 15 minutes. When the scheduled time to send out an ESM questionnaire arrived, NewsMoment checked the relevant participant's current news use before making its final determination of whether to issue the ESM or not, according to the rules set forth in the next paragraph. To minimize inaccurate self-reporting caused by recall bias, NewsMoment only sampled reading instances and news notifications that occurred within 30 minutes prior to the sampled moment.

With regard to what was sampled, our first priority was news reading. There are two ways to read news on NewsMoment: 1) clicking on a pushed news notification to enter a news item, and 2) entering a news item via the app's news-browsing interface. We expected that these two types of reading could be associated with different reading patterns, and thus designed an algorithm to attempt to balance our sampling across them. At a high level, if within the previous 30 minutes both types of reading had occurred, NewsMoment sampled whichever type that it had not sampled from the same participant in the immediately preceding sampling round. If only one type of reading had occurred within that same window, it sampled that one. If no reading behaviors had occurred in the previous 30 minutes, but a pushed news notification had, it sampled that notification; and if neither any reading instance nor pushed news notification had occurred, the pre-scheduled ESM prompt was not sent out.

3.2.2 ESM Questionnaire. Each of the two general types of news-reading instances mentioned earlier was associated with a different ESM questionnaire. Because participants would not necessarily read a pushed-news item immediately after receiving its notification, we asked them separately about the moment of notification arrival and the moment they entered the article. The ESM questionnaire variant that covered pushed news began by displaying information about such news’ notification, including the title that it had carried and the time it had arrived. These pieces of information were intended simply to remind the participants about the news notification that they had recently read. The rest of that questionnaire contained four parts: 1) the context of the notification-receiving moment, 2) the context of the news-reading moment, 3) self-assessment of reading performance and purposes , and 4) news-sharing behaviors. The only difference between this questionnaire variant and the other variant was that the latter did not ask any questions related to notifications.

In the notification-context section (when included) asked the participant 1) for his/her estimate of how much time s/he had spent reading the news item [21], 2) about his/her present activity [52, 106], and 3) about his/her activity’s complexity at the moment of receiving the notification [62] on a seven-point Likert scale, followed by three questions about the user-perceived opportuneness of the moment for 4) receiving the notification, 5) checking the news title, and 6) reading the entire news article, inspired by the three-stage notification handling stage proposed by [95]. The news-reading context section (which was present in both questionnaire variants) followed the same flow and the same set of questions. When both context sections were included in an ESM questionnaire, to decrease the burden on the respondents, they were allowed to declare that the moment when they read the news was the same moment at which they received its notification; and if they made such a declaration, then they could skip the news-reading context section.

In the self-assessment part (both questionnaire variants), the respondents self-assessed their reading performance and reading purposes. Because repeat reading could have different effects from first-time reading, it first asked them whether it was the first time they had read the sampled news content. Then, it asked them to rate the coverage of their reading on a 10-point scale, and this was followed by eight questions covering their level of engagement with [54, 57], comprehension of [38], and interest in the news article, and its relevance, complexity, authenticity, accuracy, and believability (as shown in Fig. 1d) [4]. Finally, they were asked about their reading purposes; the contextual factors they thought had influenced why they read the sampled news in the chosen way; whether they shared the news item or not; and why and how they shared the news, if they said they had done so.

At the end of each day, one hour before the end of the window participants had set for receiving questionnaires, NewsMoment also issued a diary questionnaire that contained information about the ESM they had answered, and four questions about the participants’ overall reading experience of that day. Further details of that questionnaire have been omitted, however, as no data from it have been analyzed in the current paper.

3.3 Study Procedure

Prior to data collection, due to the COVID-19 pandemic, the researchers explained the study procedure via videoconferencing, and asked the participants to sign their consent forms online. Then, the researchers remotely helped them to install the app on their phones, and checked if there had been any installation or compatibility problems by setting several tests during the experiment explanations. Then, the researchers briefly introduced NewsMoment and helped them finish adjusting its settings. NewsMoment started delivering ESM questionnaires on the first day following successful installation, and continued doing so for at least two weeks. After their participation, we also conducted 30-minute semi-structured interviews with a total of 17 participants. Unfortunately we could not present these qualitative results, due to the page length concern. For every ESM or diary questionnaire that they completed, the participants received NT14($approximately US0.50$), and for being interviewed, they received an additional NT150($approximately US5$).

3.4 Recruitment and Participants

We recruited participants via advertisements posted on social-media pages, including ones for recruiting participants and survey respondents in Taiwan. We sought participants 1) who were currently using news-aggregator apps, such as Google News or Yahoo News, or at least one of the nine news apps, in their daily lives; and 2) who received pushed news notifications from these apps in their daily lives. A total of 32 participants participated in the study, but three of them withdrew due to smartphone technical problems. Of the remaining 29, 15 were students, and the rest had a variety of occupations. They were aged from 20 to 42 (M = 26.35, SD = 5.7); 11 were females and 18 were males. All participated in our study for at least two weeks. Of the 17 interviewees, five were females and 12 male.

3.5 Data Cleaning and Analysis

We received a total of 2,635 completed ESM questionnaires, and NewsMoment logged 7,115 news-reading instances. Among the questionnaires, 73 (0.03%) were markedly inconsistent with phone logs regarding when the sampled news articles had been read. Because we were unsure if the other self-reported information these 73 questionnaires contained was reliable, we excluded them from data analysis. An additional 87 ESM questionnaires were excluded because the respondent had answered "yes" to the question of whether they had read the same news before, for the reason mentioned above. Thus, our final dataset contained 2,475 ESM responses. On average, each participant answered 85.3 ESM questionnaires (Max = 160, Min = 30, SD = 31.6).

Among the 7,115 news-reading instances, we removed instances where the dwell time was too short (351 instances being below 1 second), too long (five exceeded 10 minutes), which we considered as accidental entry and outliers, respectively. We also removed 90 news-reading instances in which system logs showed that the page did not successfully load the content. Our final dataset contained 6,669 news-reading instances from the participants (M = 230, max = 906, min = 48, SD = 194.9). Of these, 1,797(26.94%) were entered from the browsing interface in NewsMoment, and 4,872(73.06%) were entered from pushed news notifications.

Quantitative analysis relied on mixed-model regression, which is used to examine the effects of factors on an outcome of interest, such as the effect of reading mode on reading outcome. For binary predicted variables (e.g. examining likelihood), we used logistic regression. Because every participant contributed repeated observations, we included a random effect to account for individual differences' effect on the outcome. We also employed a chi-square test of independence to examine the associations between pairs of factors, such as initiation of news reading on the occurrence of a particular reading mode.

Since we observed slight differences in the classification of news categories among the nine news sources in NewsMoment, to make the category coherent and comparable, two independent coders coded the categories of the news participants reported reading in ESM. First, we kept the category of "breaking news" for all news items originally associated with it, due to its particular meaning. Then, we followed the majority rule, i.e. adopting the category from the majority of nine news sources, and applying that category to the news items about that events/issue or highly similar ones. When there was no majority, we discussed its category according to the category schema in the literature [78, 98]. We examined the inter-coder reliability on a subset (11%) of the data using Cohen's Kappa, which was 0.886, indicating high reliability between the two coders' categorization. All differences in their codes were discussed by the two coders until an agreement was reached. The coders then coded the rest of the data independently. At the end, the nine categories were: Politics, Global, Society, Life, Sport, Entertainment, Economy, Technology, which was similar to prior research [24, 30]

4 RESULTS

4.1 Mobile News Behavior

We first show the overall pattern of news reading on NewsMoment. Then, we describe the four reading modes among 6,669 reading instances, which are distinguished using clustering analysis.

4.1.1 Overall Mobile News Behavior. Participants, on average, spent 20.14 seconds on the news articles on NewsMoment (SD = 35.01), in an average scrolling speed 2.67 viewports/sec. The standard deviation in their scrolling speed was large, the average is up to 5.67 viewports/sec, suggesting varying scrolling behaviors within an article. Up to 35% of the time participants scrolled less than half of the coverage. The number of scrolls in the news article was also diverse (M = 4.54, SD = 5.58). Given the large diversity of participants' reading behaviors using NewsMoment, clustering techniques was used to distinguish them, as presented below.

4.1.2 Four Distinct News Reading Patterns. After scrutinizing all the data we collected from participants and reviewing the literature with similar attempts on classifying news reading patterns [29, 44], five features that describes the reading behavior in a reading instance were chosen for clustering, including: *dwell time*: the amount of time the user dwelled; *Coverage*: the percentage of the viewports at which users stay longer than one second; *# of scrolls*: the number of scrolls; *scrolling speed*: the number of viewports per second; *std of speed*: the standard deviation of the speed, which captures how varying the users' scrolling speed was. Its noteworthy that coverage is different from page depth [29] in that it considers the amount of time participants stayed at each viewport.

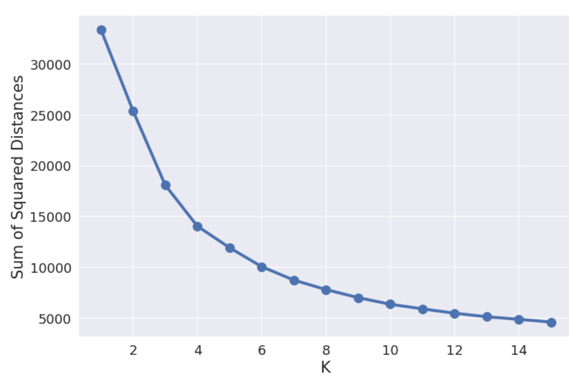
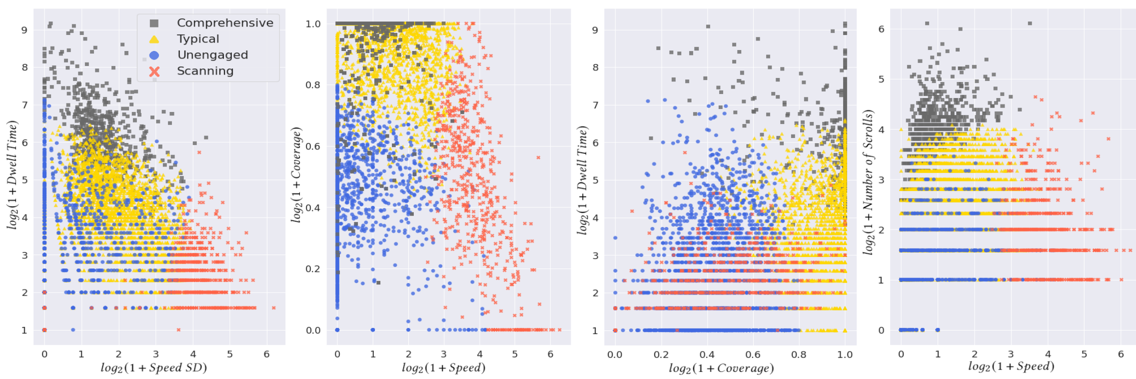


Fig. 2. Elbow Method For Optimal K

Table 1. Four reading modes with their descriptive statistic

Reading Mode	# of Scroll	Speed	Speed *SD*	Dwell Time	Coverage(%)	Page Depth(%)
Comprehensive (10.0%)	15.55 (*SD* = 8.49)	1.06 (*SD* = 1.17)	2.37 (*SD* = 2.21)	86.84 (*SD* = 73.74)	0.93 (*SD* = 0.17)	0.96 (*SD* = 0.14)
Typical Reading (47.6%)	5.05 (*SD* = 3.32)	1.90 (*SD* = 2.00)	3.39 (*SD* = 3.01)	18.02 (*SD* = 14.48)	0.92 (*SD* = 0.13)	0.97 (*SD* = 0.09)
Unengaged (33.34%)	0.72 (*SD* = 1.35)	0.54 (*SD* = 1.74)	0.71 (*SD* = 1.98)	7.23 (*SD* = 12.85)	0.31 (*SD* = 0.18)	0.45 (*SD* = 0.23)
Scanning (9.0%)	3.75 (*SD* = 3.11)	16.33 (*SD* = 10.42)	16.52 (*SD* = 9.45)	5.05 (*SD* = 4.40)	0.40 (*SD* = 0.24)	0.97 (*SD* = 0.12)

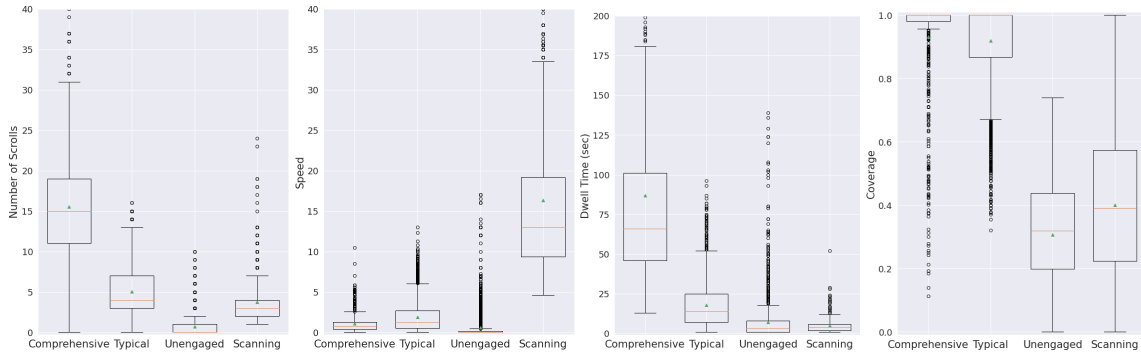


(a) Speed *SD* and Dwell Time (b) Speed and Coverage (c) Coverage and Dwell Time (d) Speed and Number of Scrolls

Fig. 3. 2-dimensional scatter plots of the clustered data across the 5 dimensions on a logarithmic scale (a) Speed *SD* and Dwell Time, (b) Speed and Coverage, (c) Coverage and Dwell Time, and (d) Speed and Number of Scrolls

4.1.3 Identifying Reading Modes on NewsMoment using Clustering. We used the k-means clustering algorithm [90] with the aforementioned features to distinguish among participants' reading behaviors. To find the optimal number of clusters K, we iterated K from 1 to 15 and used an elbow method [42] to choose K that minimized the sum of the square distance from each point to its assigned center. As Fig. 2 shows, the elbow point is at $K = 4$, meaning it is no longer worth the additional cost to divide these data more than 4 clusters. In the rest of the findings, we focused on the four reading modes derived from clustering.

4.1.4 Comparison of the Four Reading Modes. Fig. 3 shows the resulting four clusters, and Table. 1 shows the resulting four clusters' descriptive statistics. Fig. 3 shows the distribution of the points being projected in a two-dimensional space on a logarithmic scale of these features. Each point in the figure represents a news reading instance, colored according to the assigned cluster. For instance, Fig. 3b shows how the four clusters vary in coverage and scrolling speed; Fig. 3c indicates that a large dwell time does not necessarily lead to great coverage. The high distinctiveness among these reading modes can also be seen from Fig. 4, which draws the boxplots of the features. Below, we describe the characteristics of the four reading modes using these features.



(a) Number of Scrolls (b) Speed (c) Dwell Time (d) Coverage

Fig. 4. The box plots represent different distribution of each reading mode on four features respectively. The lines on the box plot represent the lower quartile, median, upper quartile, and the interquartile range of the feature (a) Number of Scrolls, (b) Speed , (c) Dwell Time , and (d) Coverage

Cluster 1: Typical (47.6%, n = 3174) was the most typical reading pattern on NewsMoment, as it occupies the largest portion and tends to be moderate in all dimensions, without distinct characteristics in specific dimensions. When using this reading mode, 87.1% of participants scrolled to the end and 58.8% of them achieved 100% of the article coverage. It had the second-longest dwell time, 18.02 seconds on average.

Cluster 2: Comprehensive (10.0%, n = 668) indicates that the participants’ reading of the news was comprehensive. With 85.8% scrolled to the end, 72.2% of the time participants achieved 100% of the article coverage, and had the longest dwell time (86.8 sec, SD = 73.7), which is 4.81 times longer than the second-longest reading mode. In Addition to time and coverage, the comprehensiveness of the reading can be best seen from the number of scrolls, which is 3.1 times larger than the second-largest mode.

Cluster 3: Scanning (9.0%, n = 603) occurred the least often, indicates a rapid and sporadic news reading where the participants quickly scrolled through the news article; however, the average reading coverage was only 40%, since most of the content was rapidly scrolled through. Participants’ scrolling speeds within the article significantly varied. That is, when scrolling through the article, instead of being at a similar speed, participants sporadically stayed at a certain part of the article shortly to read specific text and then continued scrolling, most of the time to the end (88%). This shows one type of insufficient processing and shallow reading of news articles.

Cluster 4: Unengaged (33.34%, n = 2224) was the second largest group. It describes that participants opened the news article but were unengaged in reading it. 65.2% of the time they did not scroll at all and left the news. Only 33% of the time they scrolled at least to the half. Consequently, it had the lowest coverage, number of scrolls, and scrolling speed. Participants generally left the news soon after entering it, but occasionally remained on the first page without any action, causing a relatively large variance in their dwell time, likely due to inattention. Given that participants often did not scroll to read the content, we consider it to be a shallower reading mode that induces insufficient processing of the news articles.

Fig. 5 presents how the four reading modes differed in participants’ average dwell time at each viewport position, also inspired by [44]. Compared to the other deeper reading modes, the dwell time of Scanning is nearly zero until certain points where the participants stopped at the text they wanted to examine. In contrast, participants who adopted Unengaged reading only stayed in the first 20 viewports (approximately the first page) and rarely scrolled further.

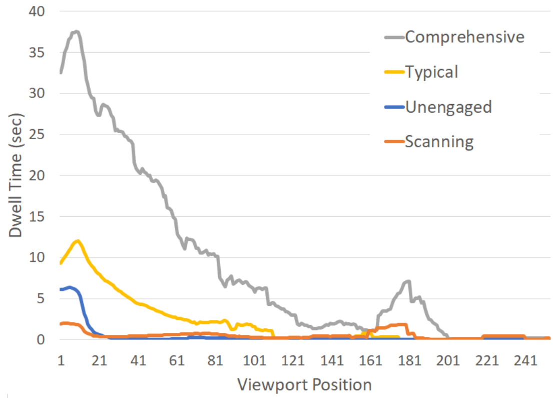


Fig. 5. Mean dwell time at different viewport positions for each reading mode

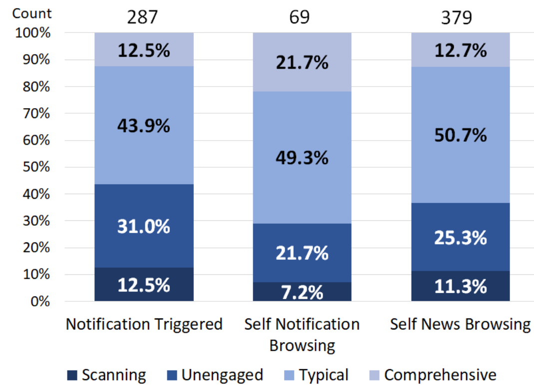


Fig. 6. Reading modes across types of initiation

4.1.5 Initiation of News Reading: News App vs. Pushed News. We investigated if a particular reading mode was more likely to be associated with certain triggers—1) *Notification-triggered*: being triggered by pushed news notifications, 2) *Self-notification browsing*: being self-initiated while browsing notifications in the notification drawer, and 3) *Self-news browsing*: being self-initiated while browsing news in NewsMoment. Starting from this section, we mainly used ESM data because logs from NewsMoment only allows us to know whether users entered the news within NewsMoment or from pushed news notifications and do not distinguish between the former two types. As Fig. 6 shows, the two shallow reading modes were more likely to occur when the news reading were notification-triggered (Total: 43.5%, Unengaged: 31.0%, Scanning: 12.5%) than self-notification browsing (Total: 28.9%, Unengaged: 21.7%, Scanning: 7.2%), and self-news browsing (Total: 36.6%, Unengaged: 25.3%, Scanning: 11.3%). A chi-square test of independence showed that the association was statistically significant $\chi^2 = 6.15$, $p = .0046$).

4.1.6 Choice of Reading Mode by News Category. We examined whether participants were more often to adopt specific reading modes when reading certain news. Generally speaking, participants were more likely to adopt shallow reading modes when they read the news of these three categories: Global (49.3%), Life (43.7%), and Breaking (39.7%) than the others ($Z = 3.932$, $p < .0001$), as shown in Fig 7.

Furthermore, we examined reading mode by initiation type and news categories. As shown in Fig. 7, there were differences between notification-triggered and self-initiated news reading. For example, when the news being read by the participants were Breaking (notification: 46.7%, self: 32.4%), Entertainment (notification: 50%, self: 21%), Global news (notification: 61.8%, self: 37.8%), and Life (notification: 50%, self: 39.8%), they were more likely to adopt shallow reading modes when the reading was notification triggered than when the reading was self-initiated ($Z = 2.726$, $p = .006$). However, when news being read concerned Politics (notification: 26.4%, self: 40.5%) and Society (notification: 17.7%, self: 38.8%), shallow reading modes were less often adopted when the reading was notification triggered than was self-initiated. Although the effect was marginal at the significance level of .05 ($Z = -1.899$, $p = .0575$). Similarly, Unengaged reading was also less likely to occur on Society news when they were notification-triggered (5.9%) than when they were self-initiated (30.6%, $Z = -1.789$, $p = .0736$). We note that although the differences were not statistically significant at the significance level of .05, it could be due to the relatively small sample size. We deem that these differences were nontrivial and noteworthy. We also note that Unengaged reading also seemed to be more likely to

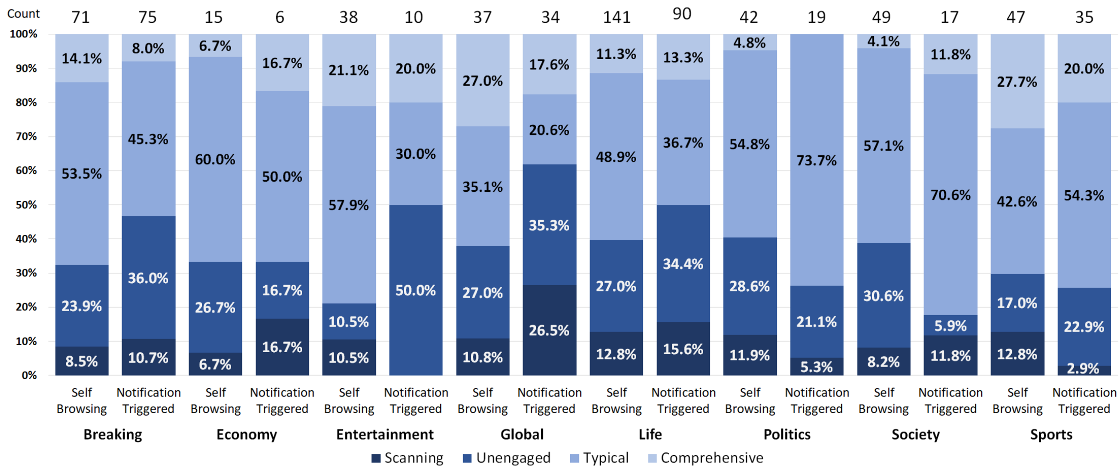


Fig. 7. Occurrence of reading modes across news categories

occur on Breaking news when they were notification-triggered (36%) than self-initiated (23.9%). If this holds true, it suggests that reminder for news audiences might be necessary if the news is crucial. However, the effect also does not meet the significance level (Z = 1.634 , p = .1023). We think future research should further look into this difference.

4.2 Influence of Moments on Pushed News Reading

Here , we examined how moments of pushed news delivery affect news reading. Thus, we mainly focused on notification-triggered news reading instances. The distribution of the four reading modes among these slightly differed — Comprehensive: 12.6%, Typical: 44.2%, Unengaged: 30.5%, and Scanning: 12.6%. Compared to the new overall distribution, the percentage of Scanning reading mode was higher, but the overall percentage of shallow reading is very similar.

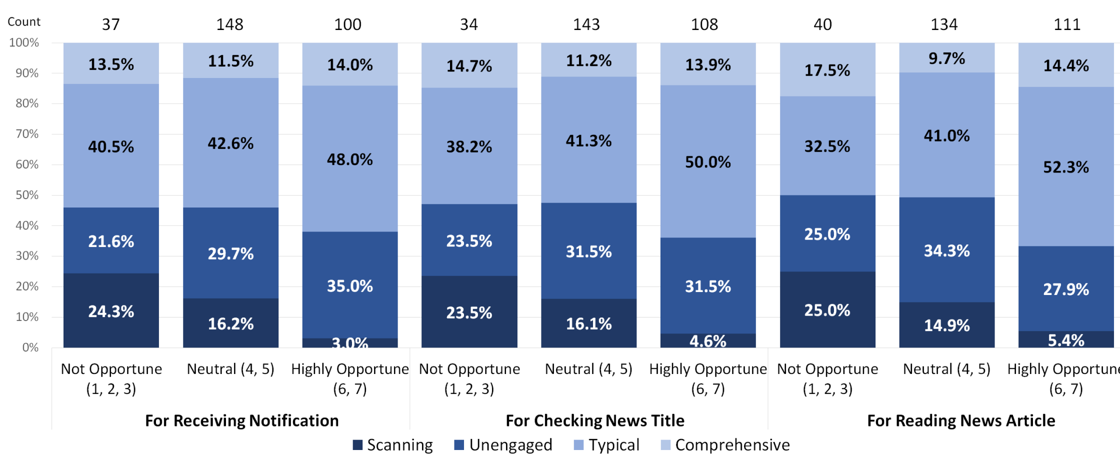


Fig. 8. Reading modes across different perceived opportuneness of the moments

4.2.1 Influence of Perceived Opportuneness of the Moment. Fig. 8 shows the results of the three kinds of opportune moment — for receiving notification, for checking the news title, and for reading the entire article — each of which was classified into three levels: highly opportune (6,7), neutral (4,5), and inopportune (1,2,3). Our results indicate several interesting relationships between the perceived opportuneness of the moment and reading mode. First, the figure shows that participants were more likely to adopt deeper reading modes at the opportune moments for checking news tiles (Z = -2.046 , p = .0407) and for reading the entire article (Z = -2.470 , p = .0135), than otherwise, but there is no substantial difference in the likelihood of deep reading mode between inopportune and neutral moments. But the difference between the opportune moment for receiving news notifications and otherwise was not statistically significant (Z = -1.417 , p = .156). Also, there is no substantial difference in the likelihood of deep reading mode between inopportune and neutral moments. This suggests that detecting opportune moments for reading articles is more worthwhile than detecting inopportune moments and avoiding them.

Interestingly, when further examining shallow reading modes, we found that the total lower likelihood of shallow reading was mainly attributed to the dramatic drop of the likelihood of Scanning reading mode. That is, the likelihoods of adopting Scanning reading, for all three kinds of inopportune moments, were four times above those at their counterpart highly opportune moments and the difference was statistically significant (Z = -2.44 , p = .0147). These results suggest that the impact of the perceived opportuneness of the moment for pushing news notifications on the occurrence of Scanning reading is enormous. Contrarily, Unengaged reading was still prevalent at the opportune moments for receiving notifications and for checking news titles, respectively. The likelihood of the Unengaged reading mode at the opportune moments for receiving notifications was even among the highest (35%). This indicates that the opportune moment for receiving notifications is actually not ideal for reading pushed news, as it may induce a high likelihood of Unengaged reading, the mode involving the least processing of news information. It is unexpected to observe the low likelihood of Unengaged reading at perceived inopportune moments. We suspected that it was likely that at these moments, participants were more selective on the news they wanted to read, and thus news that were perceived unnecessary to read might be filtered out. In the next section, we will look more into their assessment of pushed news.

4.2.2 Self-reported Interest, Purpose, and Influential Factors in News Reading at (In) Opportune Moments. Fig. 9 divides the proportion of each mode of reading into three levels of interest in the news items: high interest (6,7), medium interest (4,5), and low interest (1,2,3), with a darker color indicating higher interest. We especially note the distinct pattern between Scanning and Unengaged reading across moments. The highest percentage of Unengaged reading was associated with high interest in the news at inopportune moments, whereas at these moments, Scanning reading was rarely associated with high interest in the news; instead, it was mostly associated with low interest in the news, up to 60% particularly for reading the entire news article. While it might seem counter-intuitive that individuals read news in which they were uninterested, we note that it actually made sense for such reading at an inopportune moment. That is, given that these moments were perceived as inopportune, participants tended to be selective at these moments. Since Scanning reading was not driven by interest, it was likely to be driven by perceived necessity (e.g. importance or urgency); and due to this perceived necessity, participants quickly scanned the article to overview the news instead of leaving on the first page. This helps explain why the percentage of Scanning reading could turn into deeper reading at the opportune moments for reading the entire article, suggesting that once they had more time, they would read them more thoroughly; but, when reading was driven by interest, e.g., Unengaged reading, it is likely to remain Unengaged at opportune moments; after all, the majority of the Unengaged reading at opportune moments were also driven by interest, as shown in the figure.

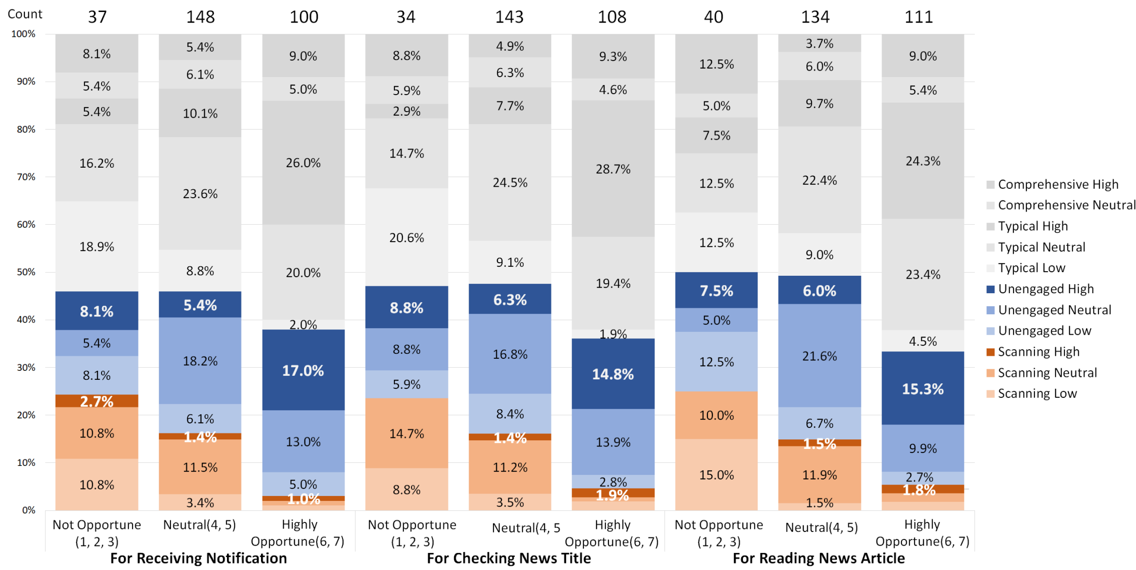


Fig. 9. Reading modes divided by the level of interest across different perceived opportuneness of the moments

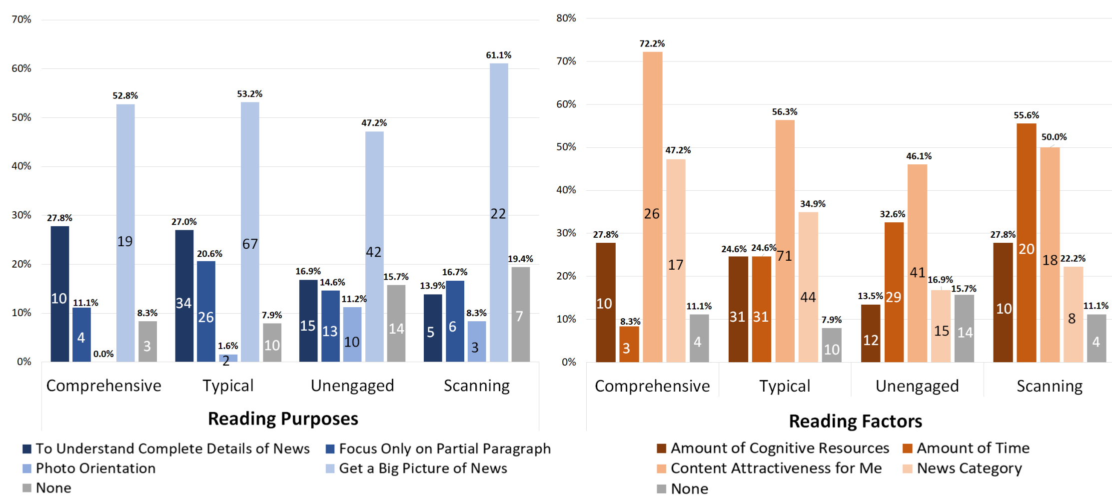


Fig. 10. Self-reported purpose of reading pushed news (Left), and factors they thought made them choose the current reading mode(Right)

Fig. 10 shows self-reported purpose, when adopting Scanning reading, participants 61% of the time mentioned the purpose “get a big picture of the news” which was a multi-choice check-box question. In terms of the factors they thought that made them choose the current reading mode, when adopting Scanning reading, they were significantly more likely to mention "the amount of time" (55.6%) (Z = 2.012 , p = .0442) than the other reading modes. These indicate that participants perceived adoption of Scanning reading was mainly due to these limited resources. In contrast, when participants used the other three reading modes, the top-mentioned factor was content attractiveness. These results suggest that although the two shallow reading modes were similar regarding dwell time and content coverage, Scanning reading was quite distinct from Unengaged reading in nature.

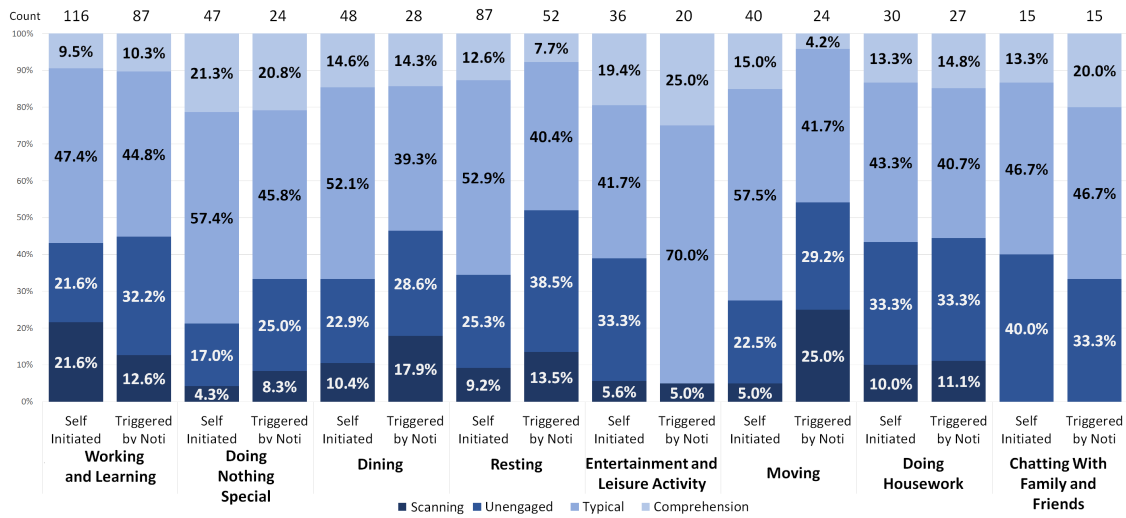


Fig. 11. The distribution of reading modes across activities

4.2.3 Reading Modes across Activity Contexts. We observed a quite diverse distribution of reading modes across different activities. We compared these reading modes with modes that were self-initiated, since they might indicate a self-identified opportune moment for reading news. We classified three types of activity. The first type is activities we deem less appropriate for push news, because the overall percentages of shallow reading between notification-triggered and self-initiated were similar in these two activities, suggesting that improving the moment of notification delivery might not increase the overall likelihood of deep reading. They were: doing housework (notification: 44.4% vs. self: 43.3%) and working and learning (notification: 44.8% vs. self: 43.2%). Both activities likely needed concentration and the break time was also limited.

The second type is activities we deem more opportune for push news, as in these activities, participants were more likely to perform deep reading when the reading was notification-triggered than when it was self-initiated (Z = -1.908 , p = .0564). These activities were: entertainment or leisure (95%) and chatting with family or friends (66.7%). Since participants were already more receptive to reading pushed news during these activities, these were relatively opportune moments and thus would need no improvement. On the other hand, it is unexpected to observe a lack of Unengaged reading on notification-triggered news reading during entertainment/leisure activity, while self-initiated ones still involve a typical amount of Unengaged. Possibly during this type of activity, participants were particularly highly receptive to the notifications sent to them. On the other hand, during all the 30 instances of social interaction, participants did not perform any Scanning reading, implying that during this type of activity, limits of cognitive and time resources were not a concern to them. They conducted more Unengaged reading possibly due to the concern of social appropriateness [50], which however, was not examined in our ESM questionnaire.

The third type is activities within which we consider future research can seek to detect breakpoints to improve the effectiveness of the delivery of pushed news. In these activities, participants were more likely to perform deep reading when the reading was self-initiated than when the reading was notification-triggered(Z = 2.84 , p = .004). These included: doing nothing particularly (notification: 33.3% vs. self: 21.3%), dining (notification: 46.5% vs. self: 33.3%), resting (notification: 52% vs. self: 34.5%), and moving (notification: 54.2% vs. self: 27.5%). The differences in these likelihoods of deep reading clearly distinguishes between moments suitable and unsuitable for reading news, indicating that detection of opportune moments within these activities may potentially help turn the existing shallow reading of pushed news into deep reading.

4.3 Self-Assessed Reading Engagement, Comprehension, and Perceived Credibility of Pushed News

Finally, we examine participants’ self-assessments of their reading engagement, comprehension, and the credibility of pushed news, respectively.

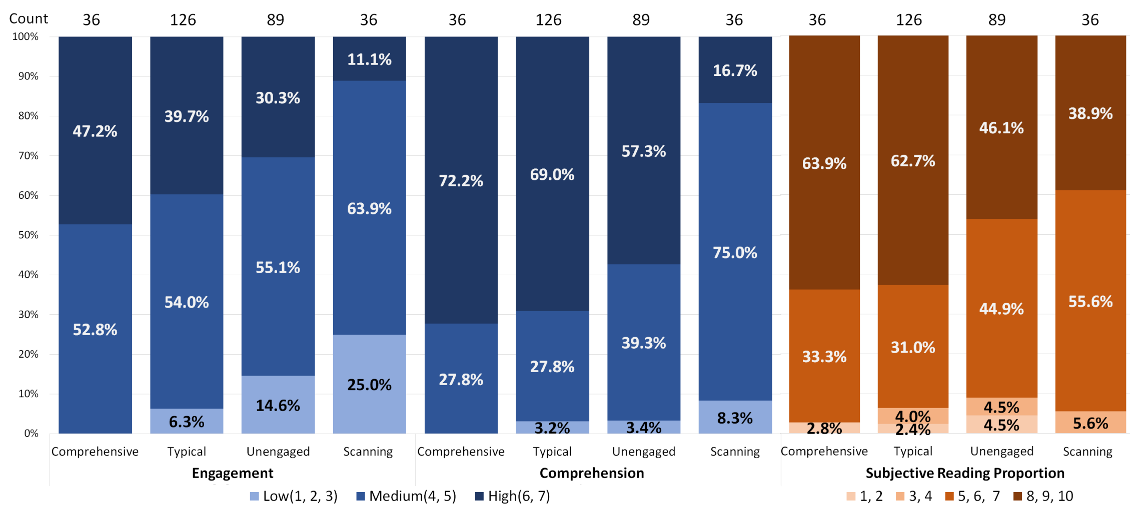


Fig. 12. Participants’ assessment of their own reading proportion, engagement, and comprehension in each news reading instance

4.3.1 *Self-Assessed Reading Coverage, Engagement, and Comprehension of Pushed News.*

Overall, among notification-triggered new-reading instances, as Fig. 12 shows, 54.7% of the time participants reported their reading proportion (on a 10-point rating scale, each step representing a 10% of coverage) of news articles as above 80%; and up to 93.4% of the time they reported as reading more than half. Such an estimation induced that, on average, their self-rated proportion of reading is 7.53 (75.3%) out of 10. However, our log analysis showed that only 67.2% of the time the participants reached 50% of coverage of the news articles if they ever read them. Participants’ particularly overestimated their reading coverage when they adopted Unengaged reading, where they reported up to 91% of the time they read at least half of the content. 46.1% of the time they even reported reading 80% of the content when using Unengaged.

Self-assessment of engagement and comprehension appeared to also be high in both of these measures. Up to 75% and 85.4% of the time participants reported at least medium engagement for Scanning and Unengaged reading, respectively. It is noteworthy that participants rarely self-rated to be highly engaged in reading when they used Scanning (11.1%), whereas, again surprisingly, when using Unengaged reading, they nearly one-third of the time (30.3%) deemed them highly engaged in reading. However, we found that these highly-rated engagement was mainly contributed by a few participants, and thus the difference was not statistically significant ($Z = 1.007$, $p = .313$). That being said, however, the possibility that users are likely to self-perceive as highly engaged in reading news articles while they were actually not should be important to note.

Participants were also optimistic in their self-assessed comprehension; participants' likelihoods as at least medium comprehension of the news were up to 91.7% and 96.6% for Scanning and Unengaged reading mode, respectively. Especially, they self-assessed as highly comprehending the news 57.3% of the time when they adopted the Unengaged mode, although it was the most shallow reading mode. Thus, we deemed that these news reading, involving objectively low engagement but subjectively high engagement and comprehension, indicate an opportunity for news-pushing mechanisms to help reduce potentially negative societal impacts caused by these optimistic self-assessments of news reading.

4.3.2 Perceived Credibility of Pushed News. Finally, participants' self-assessed credibility of the pushed news they read further reinforces our observation that Scanning is a unique reading mode. When adopting Unengaged reading, participants were at least 3.5 times as much likely to perceive that the news articles were credible (Authenticity: 59.6%, Accuracy: 57.3%, and Believability: 59.6%) as when they adopted Scanning reading mode (Authenticity: 16.7%, Accuracy: 13.9%, and Believability: 16.7%). When adopting the Scanning reading mode, participants were nearly four times as much likely to perceive that the news articles were not credible (Authenticity: 8.3%, Accuracy: 11.1%, and Believability: 13.9%) as when they adopted Unengaged reading mode (Authenticity: 2.2%, Accuracy: 2.2%, and Believability: 3.4%). However, again, the differences were not statistically significant ($Z = 1.397$, $p = .16$) because nearly half of the ESM responses reporting high-perceived credibility were from the same participant (25 out of 53). But again, despite no statistical significance being found, we deem these differences to be non-trivial and need further research with a larger sample-size. In case this pattern existed, it implies that participants were more suspicious/skeptical when using Scanning reading than when using Unengaged reading. And we deem that this is likely, since we have shown earlier that Scanning was rarely driven by interest but by other intents. Consequently, it was likely that sometimes the choice of using a Scanning reading mode had been determined upon seeing the title of the news, for the sake of examining the article rather than learning from it.

5 DISCUSSION

5.1 The Two Distinct Shallow Reading Modes: Unengaged and Scanning

Our results indicate four types of reading modes of participants on NewsMoment using the clustering technique. Despite the similar number of reading modes identified using the same clustering technique with similar features, the characteristics of the reading modes identified in our research differ from those identified in previous works on online news reading [29, 44]. For example, they referred to quick reading (dwelling on the page below 10 seconds) as *bounce*. Reading instances longer than 10 seconds but consuming less than 50% of the content were categorized as shallow reading [44]. Possibly because our reading instances were taking place on mobile devices, where a larger proportion of the reading instances were entered from notifications (73.1%), we observed two types of reading modes: Unengaged and Scanning, which were both short, with low coverage of the news article.

More crucially, although the two reading modes were both shallow, they were highly distinct, not only in their objective properties such as scrolling speeds, covered page depth, prevalence, but also in their associated triggers,

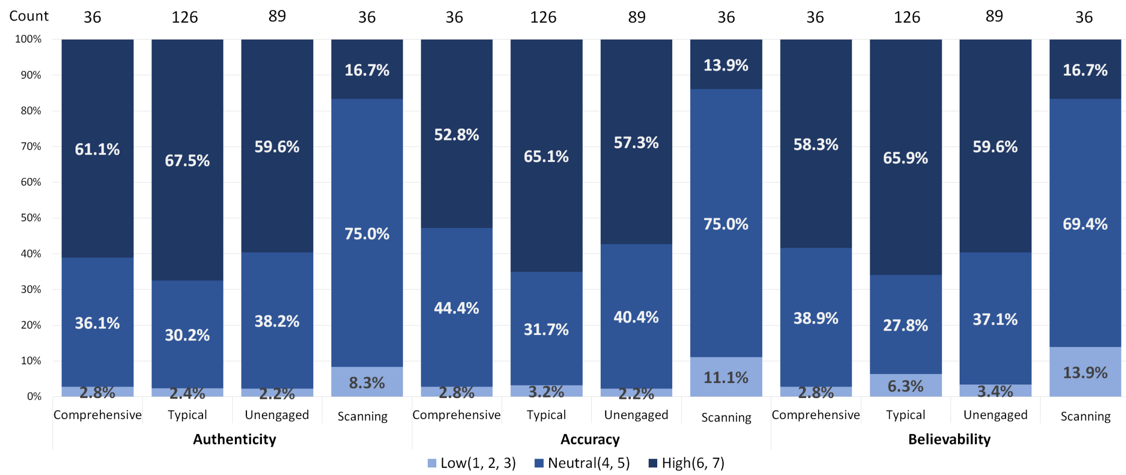


Fig. 13. Participants’ assessment of the news items’ perceived credibility

opportune moments, and very possibly also self-rated reading engagement and news items’ perceived credibility. Specifically, Unengaged reading was prevalent at both inopportune and opportune moments. But meanwhile, it is also a reading mode more likely to be manipulated. It is because while participants read the least content in this mode, ironically, they were likely to overrate their reading proportion and engagement than using Scanning reading. They were also optimistic in their comprehension and thought the news to be more credible than when using Scanning reading. Despite the possibility that the choice of this mode can be ascribed to the characteristics of the news where the content was presumably mostly credible, misinformation is also often embedded in these news [40]. The fact that they were optimistic in their reading engagement and the credibility of news without actually reading the content makes it the most likely to be subject to manipulation such as embedding misinformation in the later part of the news. It is especially because Unengaged reading was sufficiently likely to occur in the reading of breaking news that were notification-triggered than self-initiated, a kind of news considered to be societal impactful [48].

In contrast, the Scanning reading mode was much less prevalent and was not driven as much by interest as Unengaged reading; instead, when participants conducted this reading, they mostly rated low interest in these news. Furthermore, unlike Unengaged reading that was prevalent both at inopportune and opportune moments, Scanning was at least four times more likely to occur at inopportune moments than at opportune moments, and that this reading mode seems to perfectly convert into deeper reading at the opportune moments for reading news articles. Presuming that participants might be more selective at notifications at inopportune moments, such as reading more urgent and important ones [100], and that trigger of Scanning reading was not interest, we suspect that participants scanned the article for other initial intents, such as checking or scrutinizing the news out of suspicion, rather than learning from it, such that they scrolled through the article but stayed at specific parts of the article to examine the text.

Although we cannot firmly conclude about their level of suspicion and intent when adopting Scanning, given the data we have, the different mindset of reading news in Scanning from Unengaged is crucial, since it is influential on the decision of how to address these two different shallow reading modes. After all, when using this mode of reading, the news audience may have been suspicious of the news content, making them presumably less likely to be manipulated.

Notably, uncovering the uniqueness of this shallow reading mode would not have been possible if we had not associated their logged reading patterns with their in situ self-assessments in ESM. Thus, unlike previous studies that focused on describing the objective properties of reading patterns, our crucial contribution is further distinguishing between Unengaged and Scanning reading. And we argue that such distinction is critical, as these two modes are associated with different opportune moments and at different levels of risk of unintentionally facilitating misinformation dissemination. However, our speculation of the intent and mindset behind Scanning requires further verification by more research.

5.2 Opportune Moment for Pushed News Delivery on Smartphones

Our results show that participants were more likely to adopt deeper reading modes at opportune moments than otherwise, but little difference exists between such likelihoods at inopportune and neutral moments. This implies that it may be more worthwhile to detect opportune moments for pushing news than to detect inopportune moments to avoid them.

Crucially, as mentioned earlier, as opposed to that Scanning mainly occurred at inopportune moments. Unengaged reading was also prevalent at opportune moments, especially those for receiving notifications and checking news titles. This result is crucial as it clearly indicates that the opportune moment for receiving notifications is not ideal for pushing news, since it may inadvertently cause users to adopt Unengaged reading. This finding resonates with our assumption that the opportune moment for news reading is not simply about getting to know the existence of the notification, but to induce sufficient processing of news information. It also resonates with the multi-stage characteristics of the notification responding process, that glancing at the notification does not necessarily guarantee engagement [93]. Nevertheless, we deem engaging in news articles crucial, and thus suggest that, to increase the likelihood of deep reading, it is necessary to push news notifications at the opportune moments for reading the entire article. We encourage future interruptibility research to continue in this direction to detect opportune moments for reading news articles, as similar attempts (e.g., predicting moments for reading material) have been proposed [21], and because this research effort creates societal impacts. We also note that this detection is especially useful for converting Scanning reading into deeper reading, as it often occurs because users do have limited time or cognitive resources to fully process the news. Once users have enough time, the majority of Scanning reading is likely to be converted into Typical reading at opportune moment, as also discussed earlier.

5.3 Implications for Pushing News on Smartphones

Our suggestions focus on improving the existing mechanism of pushing news notification on smartphones, especially as we have shown that a great proportion of shallow reading was notification-triggered, and that certain types of news are more and less subject to shallow reading, respectively.

First, we suggest future research detect opportune moments and approach it, instead of detecting inopportune moments to avoid it, given the reasons presented earlier. Also, it is crucial to detect opportune moments for reading the entire article rather than detecting the opportune moment for receiving pushed news notifications, as the latter can inadvertently induce more Unengaged reading.

We suggest focusing on detecting two activity situations. The first is to detect activities when users are more likely to conduct deep reading, including leisure activities and during social interaction. However, while the latter might involve an issue of social breach and phubbing [3, 65], we suggest prioritizing the former activity. Prior research has explored identifying moments during social interaction [79]. We recommend practitioners to consider their approach if they aim to push news during these moments. The second is detecting opportune moments within the activities during which participants are likely to conduct deep reading, including moving, resting, mealtime. However, future research is needed to investigate opportune moments within these activities, specifically for news reading. Prior research has demonstrated the feasibility of detecting breakpoints and/or transitions within activities, and show that they are opportune moments for notifications [35, 75]. We suggest that future research should continue to build models for predicting opportune moments within these activities, particularly for reading news.

Finally, we suggest that practitioners should pay attention to the types of news that are more subject to shallow reading when they are pushed to the users' phones. Overall, we suggest news of the following categories—breaking news, entertainment, global news, and life—should be especially sent at opportune moments, as they are top categories of pushed news subject to shallow reading in our dataset. Before developing the opportune moment detection, leaving these news categories within news apps to wait for self-initiated reading may be better. As breaking news often is important and urgent to notify users, we suggest these news, especially crucial ones, come with reminders or special markers to prompt the users to read it carefully and thoroughly, given that these types of news are especially more subject to Unengaged reading when they are notification triggered.

6 RESEARCH LIMITATION

The current study is subject to several limitations. First of all, the findings are derived from a relatively small number of Android users, who were also young-skewing, and all based on Taiwan. Thus, their behaviors towards and perceptions of news may not be generalizable to older people, users of other smartphone systems, or users in other countries in which the news industry is likely to differ. Furthermore, given that our focus is on understanding opportune moments for pushed news, we had to limit the dataset to ESM responses where participants confirmed that the news reading was triggered by pushed news notifications. Had we used other methods to operationalize notification-triggered news-reading, such as using a threshold of five or six minutes [11, 20] to classify notification-triggered versus self-initiated checking, we would have a much larger sample size for the subsequent analysis, and thereby were more likely to observe statistical significance in many non-trivial differences we observed in the study.

Due to the page length, however, we could not include such analysis into this paper. While we captured other phone usage logs, we did not include them in our analysis. We also did not analyze the participants' political orientation along with the news they consumed, and it is likely that their orientation might have affected their choice of reading mode. Finally, as moments sampled by ESM have been noted as participants being relatively receptive to notifications, the obtained data might be slightly toward moments at which participants were receptive to phone notifications. We have considered this issue and extended the expiry duration for ESM (e.g., 30 minutes) to hopefully capture more unreceptive moments, and that the distribution of reading modes was only slightly different between among logged reading instances and among ESM responses. However, the fact that our ESM contained relatively more questions was still likely to over-sample receptive moments.

7 CONCLUSION

In this paper, we report on the results from an ESM study that investigated the reading behavior of smartphone-news-apps users on pushed news, with the hope that the results would enlighten us on how to inform the design of pushed news delivery. In the paper, we have presented four reading modes of our participants, two of which were shallow reading modes, but are distinct in terms of their prevalence, reading patterns, associated triggers, opportune moments, news categories, and very possibly self-assessed reading engagement and news items' perceived credibility.

In addition, we show that the opportune moments for reading the entire article are different from the opportune moment for receiving notifications and news titles, since the latter two may lead to more Unengaged reading on pushed news. We also classify three types of activity, among which one type is relatively opportune for pushing news and another type entails opportune moment recognition within activities. These findings inform our pushed-news design recommendations aimed at reducing shallow reading, and we also include categories of pushed news that are more likely to subject to Scanning or Unengaged reading, respectively.

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