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Screenertia: Understanding "Stickiness" of Media Through Temporal Changes in Screen Use

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Abstract

Descriptions of moment-by-moment changes in attention contribute critical elements to theory and practice about how people process media. We introduce a new concept called *screenertia* and use new screen-capture methodology to empirically evaluate its occurrence. We unobtrusively obtained 400,000+ screenshots of 30 participants' laptop screens every 5 seconds for 4 days to examine individuals' attention to their screens and how the distribution of attention differs across media content. All individuals' screen segments were best described by a log-normal survival function—evidence of screenertia. Consistent with the literature on uses and gratifications of media, *news/entertainment* activities were the most "sticky." These findings indicate that screenertia is not only related to the level of interactivity of media content but is also related to its modality and agency. Discussion of the findings highlights the importance of theorizing, examining, and modeling the specific time scales at which media behaviors manifest and evolve.

Keywords

intensive longitudinal data, laptop use, media attention, screenomics, survival analysis

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Verbs that describe screen use—watch, listen, interact, process—do not refer to binary states but to dynamic processes. From the time a screen is turned on until it is turned off, there is considerable variance in the information that is selected for attention and the time spent processing and interacting with that information. For example, children look at (and away from) screens numerous times per viewing session (e.g., Richards & Anderson, 2004), adults switch frequently between different tasks when using a computer (e.g., Mark et al., 2005; Yeykelis et al., 2018), and processing effort for most everyone changes second by second in response to a variety of visual and auditory cues and in relation to personal interests (e.g., Reeves et al., 1985). Given that people attend to screens for many hours per day, it is theoretically important to describe and understand the factors that drive variations in attention to screens; that is, what content attributes and interface features influence how long people dwell on a screen and how quickly they switch away from it?

New media increasingly offer greater attentional flexibility for users than traditional media. The description and influence of that flexibility on theories of attention and media effects remain underexplored. Examining the temporal variation in screen attention is critical to understanding the effects of contemporary media. There is evidence that changes in attention are related to higher arousal and better memory for information (e.g., Lang, 2000; Yeykelis et al., 2014), changes in looking at or away from a screen can influence comprehension of narratives (e.g., Calvert et al., 1982), differences in device—whether it be mobile devices or computers—impacts attention to news content (Dunaway et al., 2018), and changes in the sequencing of information, either actively constructed or passively accepted by viewers, alter emotional experiences (e.g., Mark et al., 2014; Wang et al., 2012). These and other empirical findings inform theory construction about media and technology experiences (e.g., the limited capacity model of motivated mediated messages; Lang, 2000, 2006b) and new theories about user engagement (e.g., uses and gratifications 2.0; Sundar & Limperos, 2013).

The features of media that influence attention, however, have changed dramatically over the last decade (Reeves et al., 2021), with the possibility that attentional processes now work differently than previously assumed. The range of media content available is now broader than ever before (media now include relationships, work, entertainment, money, news, transportation, and even home lighting and irrigation), consumption is fragmented (the average task on personal screens lasts only seconds), information diets are idiosyncratic (one hour of screen time is radically different from person to person), experiences are increasingly interactive (media experiences are created by users, not just passively consumed), and devices are mobile (we take our screens with us everywhere). These changes can engage users and make it easier for them to fragment and recombine media segments in ways that meet their interests (Sundar & Limperos, 2013). For instance, the amount of control users have over an interaction and the degree to which users can produce active input heightens attention (Ahn et al., 2021; Oh et al., 2018). The increased use of photos and videos compared to text also allows users to feel more a part of the mediated world, with corresponding increases in attention and engagement (Vraga et al., 2016; Yang et al., 2015). All these changes in interactivity, control, and content likely require revisions of or new theory about how media affects individuals' attention and engagement.

This paper updates knowledge of how individuals attend to interactive media with new data about everyday use of laptop computers. We focus on how selective attention is segmented by individuals as they actively change the content on their screen as they engage with different windows, websites, applications, and platforms. We examine the amount of time people dwell on content without switching to new material, a metric that has become increasingly important as metrics of media engagement shift from measures of how *many* people engage with content toward measures of how *long* people engage with content (Napoli, 2011). The study of dwell time on laptop screens is similar to the study of attentional inertia with television programs (Richards & Anderson, 2004); however, it differs in that inertia in our case does not define maintenance of attention based on gaze—that is, looking at a screen before looking at something away from the screen. Rather, inertia here is continued maintenance of attention to a screen content segment before that segment is replaced with another content segment. Stated differently, we infer that the length of time an individual spends on a specific screen reflects attention to that screen content. Screen content that generates longer times between switches (i.e., longer segments) has greater "stickiness." We call the lengthened dwelling *screenertia*, emphasizing the "stickiness" of a single segment of screen content and its effects on attention (Lin, 2007).

We conducted this research using a new data collection framework that enables near continuous recording of quickly changing attention to digital devices in natural environments. This allows us to observe and examine how attention is allocated as individuals construct their own content streams in a natural context (in contrast to how attention is allocated when individuals engage with experimental stimuli in a laboratory). We use the screenomics framework (Reeves et al., 2021) wherein screenshots of all the content appearing on individuals' screens are unobtrusively collected every 5 seconds that devices are turned on. This framework enables granular observations of actual, rather than recalled, experiences and it fills a growing need for accurate description of changes in media use that can elaborate current theories and contribute to new ones (Munger et al., 2021). The screenshot time series that the screenomics approach makes available—that is, the comprehensive observations of when each individual engaged with and switched among different tasks and media content—allows us to measure the extent of screenertia in detailed media use records and examine how screenertia differs across the increasingly diverse types of content.

In summary, this paper: (a) examines how attention changes over time, and particularly how the inertia of attention, what we refer to as *screenertia*, changes during use of laptop computers, (b) examines how the "stickiness" of attention, as indicated by the likelihood of maintaining attention once it is initially given, differs across types of content, and (c) considers how changes in attentional variance can be interpreted with respect to established theories of media behavior and to new theories that consider the dynamics and time scales of media use.

Attention and Media

How attention is measured in the laboratory. Prior research on attention and media engagement is primarily based on observations of how people watch television, gathering information about look times or physiological signals, and using those data to make inferences about how people select content and about the intensity of their engagement. For instance, Reeves et al. (1985) used the alpha frequency of EEG recordings to examine orienting responses to features of television screen content (e.g., cuts, breaks). As an alternative to physiological indicators of attention, Richards and Anderson (2004) examined look times—the length of time a child's or adult's eyes are directed toward the television screen—to examine how attention was deployed in different experimental conditions, including the presentation of scenes in narrative or randomized order (e.g., Anderson et al., 1981; Burns & Anderson, 1993; Richards & Cronise, 2000). Recent extensions of this work have used eye-tracking measures to precisely determine how attention is distributed in complex environments that more closely match real-world situations, such as when multiple devices are present (Brown et al., 2019; Holmes et al., 2012). In this study, we extend current work by using a proxy for look times on screens as a measure of individuals' attention.

From attentional inertia to screenertia. Researchers have identified systematic patterns in how people look at and engage with multiple types of media and online content. Generally, the longer people look at or engage with particular content, the less likely they are to switch from that content—a phenomenon labeled as *attentional inertia* (Richards & Anderson, 2004; Sobkowicz et al., 2013). This phenomenon is described as inertia because look times are log-normally distributed. The shape of the distribution serves as the empirical indicator of attentional inertia; that is, if attention segments were not log-normally distributed, we would not have evidence of attentional inertia. Figure 1, displaying the probability density functions of the log-normal, exponential, Gompertz, log-logistic, and Weibull distributions, illustrates this point. If attention segments followed an exponential distribution, then the probability of turning away or disengaging never changes; whether one has just begun reading a webpage or has already been reading for 5 minutes, the probability of moving onto the next webpage is always the same (a complete absence of "stickiness"). The steady rate implied by the exponential distribution is not consistent with the documented progressive maintenance of attentional engagement over time, whereas the skew and "fat tail" that characterize the log-normal distribution captures the relative "stickiness" of particular content.

The "stickiness" captured by the log-normal distribution is evident in attention segments and other behaviors across both passive and interactive media. For example, Richards and Anderson (2004) found that the overall (log-normal) distribution of look times during passive television watching was consistent across ages, studies, and other experimental factors. Although the modal look time was only 1 or 2 seconds, look times followed a log-normal distribution, the long tail of which indicates that people's

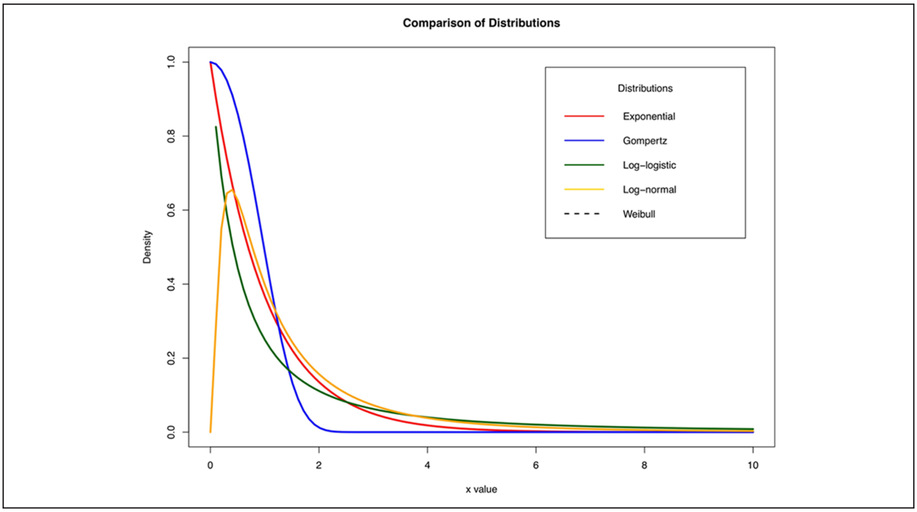

Figure 1. Comparison of different probability density functions.
Note. Each color in the plot represents one of five distributions compared in this study (i.e., the exponential, Gompertz, log-logistic, log-normal, and Weibull models).

eyes tend to stick to the screen the longer they stay there. Similarly, the length of Wikipedia articles (Voss, 2005) and comments on active online discussion forums (Sobkowicz et al., 2013) are also log-normally distributed. Although modal message length on the discussion forums is only 24 to 209 bytes (depending on the message board), comment lengths follow a log-normal distribution with a long tail, again indicating that postings become "sticky" with long posts tending to get even longer.

Notably, most research on attentional inertia in passive media and to specialized content has been conducted in laboratory settings where it is relatively easy to record and quantify the time people fix and divert their gaze to and from media stimuli. Much less is known about how attentional inertia manifests in everyday use of mobile devices. On laptops and smartphones, people switch quickly between and among many types of content, often within seconds, creating threads of use that are difficult to mimic or observe in the laboratory (Yeykelis et al., 2014). These new devices enable fragmentation of content and idiosyncrasy in use patterns that were not available in television and older media (Brinberg et al., 2021). This study examines whether and how inertia manifests in real-world engagement with contemporary interactive media. Specifically, we examine whether individuals' laptop use—that is, exposure to and engagement with particular content—also follows a log-normal distribution, and if it does, how that result should be incorporated into psychological theories of media processing.

In contrast to the original television watching studies that relied on laboratory-based observations to capture visual gaze and examine attentional inertia, we record moment-by-moment changes in screen images to observe screen content and quantify inertia in users' interactions with media. Our approach provides several advantages over prior experimental studies, including (a) increased ecological validity of media stimuli and media behaviors to a body of work that often relies on artificial manipulations and observations, (b) avoidance of inaccuracies arising from self-reported media behaviors (Andrews et al., 2015; Ohme et al., 2021) because our observations do not rely on individuals to remember fast and fragmented behaviors that are often difficult to report accurately, and (c) greater accessibility to studying attention than some eye tracking and psychophysiological approaches that require specialized training and equipment. Furthermore, prior research suggests that the time between changes in screen content indicates, or at least approximates, users' actual gaze. Less than 10% of looks are off-screen in subtitled or multi-screen contexts (Holmes et al., 2012; Jensema et al., 2000) and less than approximately 25% of gazes are off-screen when watching television with a DVR (Siefert et al., 2008). Additionally, unlike the case of passive television viewing, the screen content we capture is manifesting in interactive media, where the goals and characteristics of the user and the affordances of the screen content co-actively drive attention. Although the screen capture methodology used in the current study provides rich information about interactive media use, we cannot yet discern *who* or *what* is driving transitions in screen content. That is, the distribution of screen content exposure times is a result of user characteristics *and* media affordances that drive use. Thus, we frame our work as the study of the behavioral metric *screenertia*, rather than of attentional inertia as traditionally conceived, as a new concept to study engagement with interactive media.

Media Content and Screen Segments

Media content influences attention. For example, look times and their distribution differ depending on the content or genre of television (Geerts et al., 2008; Hawkins et al., 2005), the presence and content of other "distractors" in the environment (e.g., second screens; Brown et al., 2019; Holmes et al., 2012), or users' affective state. For example, mood management theory (Zillmann, 1988) posits that users will select and engage with media content that helps regulate their emotions. For instance, an experimental study that induced negative, neutral, and positive moods found that participants in the negative mood condition selected and listened to more energetic music for longer periods than participants in the positive mood condition (Knobloch & Zillmann, 2002). Thus, media stimuli that elicits positive or arousing states for users may be "sticky" in that they are attended to for longer periods of time.

In newer media, technological features of the platform can also influence attention and time spent on the screen content. The uses and gratifications 2.0 framework (U&G 2.0; Sundar & Limperos, 2013) explains how users' gratifications are fulfilled by both their own cognitive or emotional states and a variety of media affordances, such as: (a) modality—the sensory experience the content offers, with richer content expected to elicit higher levels of realism and novelty, and thus a more immersive experience; (b) agency—the extent to which users are able to create their own content, with higher levels of agency expected to increase engagement; and (c) interactivity—the responsiveness of the content, with more interactive content expected to generate an increase in user interest. Interactivity is of particular interest when categorizing screen content because the degree of interaction and activity afforded by the media interface may dictate users' engagement and gratifications. In this way, screenertia offers a new strategy for operationalizing the challenging concept of "affordances" and the implied co-occurrence of media features and user actions. By tracking the time spent on changing screen content, we are able to capture the culmination of user- and media-driven characteristics that dictate digital media reception, as posited by U&G 2.0.

The uses and gratifications derived from particular devices and content are hypothesized to drive the length of time users stay engaged with particular types of content. Tasks that may elicit greater user engagement and longer screen segments of consecutive content (i.e., "stickiness") on the laptop include (a) *communication* activities (e.g., social media) because users may derive high levels of agency (e.g., by creating their own profiles and generating posts) and interactivity (e.g., by sending and receiving messages and "likes"), and (b) *news/entertainment* activities (e.g., blog, entertainment website, games, music, video streaming) because users may derive gratifications from the modality (e.g., rich content from video streaming) and high levels of interactivity (e.g., playing games) of these activities. In contrast, tasks that may elicit comparatively less user engagement and shorter screen segments on the laptop include *lifestyle* activities (e.g., exercise, food, health) and *function* activities (e.g., navigation, study/work, search) because these activities do not evoke much richness in modality, agency, and interactivity. For example, Wikipedia is low in modality because it often only contains text and static images and is low in agency because most users do not contribute text/information to the site. The low level of affordances provided by Wikipedia make the site less engaging for the user and may result in shorter screen segments. In sum, U&G 2.0 informs the extent of users' screenertia when viewing specific types of interactive media content and thus informs the hypotheses stated in the next section.

The Present Study

The present study collects screenshots of individuals' laptop screens every 5 seconds that the laptop is in use (Reeves et al., 2021) to study in situ screenertia during 4 days of typical student life. First, we use parametric survival models to identify evidence of screenertia by modeling the distribution of screen segments (i.e., length of time until a user switches to a new type of content). In line with prior work on the distribution of attention in a variety of media environments (e.g., length of looks while watching television; Richards & Anderson, 2004), we hypothesize:

> H1: The length of individuals' screen segments on laptops will follow a log-normal distribution—that is, evidence of screenertia. Stated differently, we expect content to be less "sticky" when individuals initially engage with content, and content will become more "sticky" as individuals continue to engage with that content over time.

Second, we examine whether different types of screen content are characterized by different screen segment length. Building from U&G 2.0 (Sundar & Limperos, 2013), we posit that content that is rich in modality, agency, and interactivity will have greater overall "stickiness" (i.e., longer screen segments), and that content lacking in modality, agency, and interactivity will have less "stickiness" (i.e., shorter screen segments). Specifically,

H2: *News/entertainment* content (games, music, video streaming, etc.) will have the longest screen segments (i.e., high "stickiness").
H3: *Functional* content (navigation, study/work) will have the shortest screen segments (i.e., low "stickiness").

Within each of these different types of screen content, we additionally examine the relative "stickiness" of various subcategories of content.

RQ1: What is the relative "stickiness" of specific content (e.g., email, social media) within each general activity category (e.g., communication)?

Methods

The screenomics approach unobtrusively collects screenshots from users' devices every 5 seconds for many days or months using a researcher-developed software application (see Reeves et al., 2021 for an in-depth description of the approach and software). Details relevant to our examination of screenertia are described below.

Participants

Participants were 30 undergraduate students (22 women, eight men) recruited from a medium-sized university on the west coast of the US. Participants were age 19 to 23 years (M_{age} = 20.77, SD_{age} = 1.10), and reported majoring in humanities (19; 63.3%), engineering (9; 30%), and undeclared (2; 6.7%). The majority of participants rated themselves as intermediate level computer users (18; 60%), and about a fifth of the sample rated themselves as advanced users (7; 23.3%) and another fifth as novice users (5; 16.7%).

Procedure

Participants were recruited through classes to complete a study about laptop use in natural settings. Once recruited, individuals were scheduled to visit the lab on the following Monday. During their visit, they completed questionnaires, including measures of motivated cognition and motivational activation (Lang, 2006a, 2006b), and installed two custom software programs on their laptops. One program unobtrusively recorded website URL domain switches and presented a three-item questionnaire about emotions every 7 to 12 minutes after a randomly selected domain switch (these data are not examined in this study). The second program unobtrusively took a screenshot of the laptop screen every 5 seconds the laptop was in use over the course of 4 days (Monday through Thursday) and labeled the screenshot with a timestamp. System details are available upon request. Participants were instructed to use their laptop as normal and complete brief emotion questionnaires when they were presented. After 4 days (on Thursday), participants returned to the lab to complete a brief self-report questionnaire, the software programs were removed from their laptops, and the screenshot files were transferred in bulk to the study database. Participants were compensated with course credit.

Measures

The primary measures of interest were the content category of each screenshot and the length of time the participant spent with a particular kind of content before switching to something new. Each screenshot was examined and tagged by the research team using a *content* typology with 21 mutually exclusive categories that were nested within five *general activity* categories. For web behavior, coding relied on URLs, where the category was determined from website descriptions or mission statements (e.g., CNN is a "multinational news-based pay television channel"). Behaviors that did not use a web browser (e.g., Word documents) were coded based on domain-application. Consensus on classifications and resolution of discrepancies or edge cases was achieved through regular discussion among members of the coding team. Once a code was determined for a URL or behavior, all other instances were assigned the same code. When multiple applications were open on the screen, the primary window (i.e., the larger or active window) was coded. This coding scheme has high face validity, and a similar coding scheme of screenshots has been employed with high reliability (Yeykelis et al., 2014). Table 1 contains a summary of the content and general categories.

Content categories. The screenshots were first assigned to one of 21 specific categories based on domain-application. These 21 categories were *e-mail* (e.g., Gmail), *social media* (e.g., Facebook, Instagram, Twitter), *navigation* (e.g., opening a new tab, logging in), *study/work* (e.g., Microsoft Word, books.google.com), *search* (e.g., Google, Yahoo), *exercise* (e.g., healthunlocked.com, myfitnesspal.com), *food* (e.g., allrecipes.com, order.dominos.com), *health* (e.g., health.gov), *shopping* (e.g., eBay, Amazon), *blog* (e.g., AV Club, popsugar.com), *entertainment website* (e.g., Buzzfeed, US Magazine), *games* (e.g., roulette2000.com, sporcle.com), *image* (e.g., iPhoto, flickr.com), *informational website* (e.g., noaa.gov, usada.org), *music* (e.g., iTunes Music, soundcloud.com), *news* (e.g., abcnews.com, theatlantic.com), *porn* (e.g., pornhub.com, xtube.com), *video streaming* (e.g., YouTube, Netflix), *study-related* (e.g., pop-up surveys that were part of the study protocol), *unclear*, and *other*.

General activity categories. Once the specific categories were assigned, eight graduate students in media and communication organized the specific categories into general

Table 1. Distribution of Screenshot by General and Specific Category across All Participants.

Category	Number of screenshots	Total time	Proportion
Communication	*81,168*	*112.73 hours*	*0.1990*
E-mail	37,512	52.10 hours	0.0920
Social media	43,656	60.63 hours	0.1071
Function	*125,540*	*174.36 hours*	*0.3078*
Navigation	8,713	12.10 hours	0.0214
Study/work	108,488	150.68 hours	0.2660
Search	8,339	11.58 hours	0.0204
Lifestyle	*7,120*	*9.89 hours*	*0.0175*
Exercise	284	23.67 minutes	0.0007
Food	847	1.18 hours	0.0021
Health	10	0.83 minutes	0.0000
Shopping	5,979	8.30 hours	0.0147
Media	*128,989*	*179.15 hours*	*0.3163*
Blog	30,178	41.91 hours	0.0740
Entertaining website	9,856	13.69 hours	0.0242
Games	41	3.42 minutes	0.0001
Image	3,814	5.30 hours	0.0094
Informational website	9,908	13.76 hours	0.0243
Music	8,897	12.36 hours	0.0218
News	10,445	14.51 hours	0.0256
Porn	1,160	1.61 hours	0.0028
Video streaming	54,690	75.96 hours	0.1341
Other	*64,990*	*90.26 hours*	*0.1594*
Other	19,955	27.72 hours	0.0489
Study-related	36,544	50.76 hours	0.0896
Unclear	8,491	11.79 hours	0.0208
Total (all categories)	407,807	566.39	1.00

Note. All laptop use from $N=30$ undergraduate students during 4 days of study.

activity categories based on affordances (or action possibilities) of the various platforms as discussed in the U&G 2.0 framework. Five categories emerged: *communication* (e-mail, social media), *function* (navigation, study/work, search), *lifestyle* (exercise, food, health, shopping), *news/entertainment* (blog, entertainment website, games, image, informational website, music, news, porn, video streaming), and *other* (other, study-related, unclear).

Screen segment length. Working from the tagged screenshots, a sequence of consecutive screenshots in the same content category was defined as a unique "screen segment." The length of each segment was used as a measure of selective attention, defined as the length of time before an individual actively changes the content on their screen by switching between different windows, websites, applications, or platforms. Whenever a new content category appeared, a new screen segment began. For example, in determining the length of a general activity segment, a switch from CNN to Wikipedia would start a new screen segment because CNN is classified as news and Wikipedia is classified as study/work, whereas a switch from Facebook to Twitter would *not* start a new screen segment because both are classified as social media. *Segment length* was calculated for each screen segment as the number of screenshots within that segment.

Data Analysis

Distribution of screen segment lengths on laptops. We examined and modeled the distribution of screen segment lengths using a three-step procedure. First, five different parametric survival models—exponential, Gompertz, log-logistic, log-normal, and Weibull—were fit separately to each of the 30 participants' screen segment lengths. These five distributions were chosen based upon prior studies examining look times on specific media (e.g., Richards & Anderson, 2004; Richards & Cronise, 2000). Second, the best fitting model was identified for each individual using Akaike Information Criteria (lower AIC indicates better fit; Bozdogan, 1987) and interindividual differences in distributional form were described. Third, when the majority of participants (conservatively defined as >80%) had the same best fitting survival model, a stratified version of that particular model was used to describe the sample as a whole while allowing for individual differences in the location and scale parameters that describe each individual's screen segment lengths. Specifically,

$$log\left(Length_{it}\right) = \mu_0 + \beta_1 S_1 + \ldots + \beta_{29} S_{29} + (\sigma_0 + \ldots + \sigma_{29})\varepsilon_{it} \tag{1}$$

where the outcome is the length of a screen segment for individual i at time t, μ_0 is the location parameter for the reference participant (S21), β_1 through β_{29} are the deviations in the location parameter from the reference participant for the other 29 participants, S_1 through S_{29} are dummy variables for each of the other 29 participants, and σ_0 through σ_{29} are scale parameters for each participant.

The value of fitting parametric survival models goes beyond replicating analytic procedures used in prior work on attentional inertia for three primary reasons. First, compared to non-parametric survival models (e.g., Cox's proportional hazards model), the parametric survival models each imply that the within-person attentional processes of interest have specific characteristics (e.g., no "stickiness"). Second, compared to multilevel survival models, the stratified parametric survival models do not impose any normality assumptions on the distribution of between-person differences in the location or scale parameters of the within-person distributions. Finally, parametric survival models mathematically describe an underlying process using a dynamic equation that facilitates formulation of model-based predictions about the timing of behaviors, inferences about what happens under different conditions/parameters, and overall better understanding of the underlying process involved in attention switching.

Differences in content "stickiness." We next examined whether there were differences in survival time (i.e., length of screen segments for a particular content category) across types of content by including the general activity screen category variable as a predictor in the sample-level stratified survival model. Specifically, the 30 participants' segment lengths were modeled as,

$$log\left(Length_{it}\right) = \mu_0 + \beta_1 S_1 + \ldots + \beta_{29} S_{29} + \beta_{30} Function_{it} + \beta_{31} Lifestyle_{it} \\ + \beta_{32} News / Entertainment_{it} + \beta_{33} Other_{it} + (\sigma_0 + \ldots + \sigma_{29})\varepsilon_{it} \tag{2}$$

with β_{30} to β_{33} fixed across participants and *communication* serving as the reference category.

In a final set of analyses, we examined whether there were differences in survival time among the specific categories within the general *communication*, *function*, *lifestyle*, and *news/entertainment* categories. Specifically, in equation (2), *General* $ActivityCategory_{it}$ was replaced with $ContentCategory_{it}$.

All models were fitted to the data in R as parametric accelerated failure time models using the *survival* or *flexsurvreg* packages (Jackson, 2016; R Core Team, 2018; Therneau & Grambsch, 2000). Plots were constructed using the *ggplot2* package (Wickham, 2016).

Results

Over the course of 4 days, the 30 participants provided over 400,000 screenshots, documenting approximately 566 hours of laptop use. Consecutive screenshots were grouped into contiguous segments of content. Altogether, the 400,000+ screenshots were organized into 18,396 unique general activity screen segments and into 22,789 specific content category screen segments. Overall laptop use was characterized by approximately 33 unique general activity and 40 unique specific content category screen segments per hour. Aggregated screenshots and length of time spent in the content and general activity screen categories for the 30 participants is given in Table 1. Among the specific content categories, the *study/work* category was engaged the most frequently, while the *health* category was engaged the least frequently. Among the general activity categories, *news/entertainment* was the most frequent category, whereas *lifestyle* was the least frequent category. The median length of a general activity screen segment was 25 seconds, meaning that half of all screen segments were 25 seconds or less (M = 1.85 minutes, SD = 5.88 minutes, range = 5 seconds–4.82 hours). The median screen segment time of a specific content category was 20 seconds (M = 1.49 minutes, SD = 5.19 minutes, range = 5 seconds–4.82 hours).

Distribution of Screen Segment Lengths on Laptops

The distributional shape of individuals' screen segment lengths on laptops was determined by fitting five parametric survival models (exponential, Gompertz, log-logistic, log-normal, and Weibull) to each individual's screen segments. Model fits for each individual are shown in Table S1 of the Supplemental Material, with the best fitting model (i.e., lowest AIC) indicated in bold font. The log-normal survival function fit the best for all 30 participants; thus, H1 was supported. Every individual's laptop use exhibited screenertia.

Even though all individuals are characterized by the same type of distribution, there are between-person differences in location (the peak of the distribution) and scale (the thickness of the tail of the distribution). The collection of fitted distributions, and the implied location (peak) and scale (thickness of tail) parameters for each individual, are shown in the individual panels of Figure S1 in the supplemental material. The μ (location parameter that represents the peak of the distribution) for the reference participant, S21, is 1.72 (SE = 0.05), indicating a 27.92 second screen segment. The other 29 participants' location parameters deviated from the reference participant by, on average, 0.15 (SD = 0.22). Generally, the smaller the location parameter, the steeper the distribution (e.g., compare S45–S50). The average scale parameter, σ, was 0.66, with variation across participants in the amount of positive skew (SD = 0.06). The larger the scale parameter, the thicker the tail of the distribution (e.g., compare S33–S30). In sum, all individuals' laptop use exhibited screenertia, and both the length of the prototypical screen segment (location parameters) and the extent of stickiness in their media engagement (thickness of the distributional tails) differs across individuals.

Differences in Content "Stickiness"

Next, we examined how screen segment lengths differed across the general activity categories. Results are shown in Table 2. The reference group, the *communication* category and participant S21, location parameter was 1.77 (SE = 0.06), indicating a 29.35 second screen segment. Table 2 contains the estimated deviations in the location parameter for the remaining general activity categories (i.e., function, lifestyle, news/entertainment, and other) and participants relative to the *communication* category and participant S21, respectively. Consistent with H2, the *news/entertainment* category had significantly longer screen segment lengths (β_{32} = 0.18, SE = 0.03; 35.14 seconds) compared to the *communication* category. Contrary to H3, the *function* category (β_{30} = −0.05, SE = 0.03; 27.92 seconds) screen segment lengths were not significantly different than the *communication* screen segment lengths and the *other* category had significantly shorter screen segment lengths (β_{33} = −0.25, SE = .03; 22.86 seconds). Furthermore, the *lifestyle* category had significantly shorter screen segment lengths (β_{31} = −0.17, SE = 0.07; 25 seconds). These differences can be seen in Figure 2 (stratification across participants not shown), where the blue (uppermost) curve represents *news/entertainment* screen segments and the purple (lowermost) curve represents *other* screen segments. Each curve indicates the probability of a screen segment

Table 2. Log-normal Accelerated Failure Time Model Results: General Activity Screen Category as a Predictor, Location, and Scale Stratified by Participant.

Screen category	Estimate	*SE*
Communication (location)	1.76*	0.06
Function, β_{30}	−0.05	0.03
Lifestyle, β_{31}	−0.17*	0.07
News/entertainment, β_{32}	0.18*	0.03
Other, β_{33}	−0.25*	0.03
Participant	**Location (μ)**	**Scale (σ)**
S21	—	0.69
S22	0.03	0.66
S23	0.07	0.69
S28	0.15	0.67
S30	−0.15	0.73
S31	−0.15	0.70
S32	0.14	0.68
S33	0.36	0.53
S34	0.28	0.67
S35	0.12	0.62
S37	−0.26	0.72
S39	0.20	0.69
S40	0.25	0.58
S41	−0.17	0.73
S43	−0.11	0.64
S44	0.39	0.67
S45	0.88	0.57
S46	−0.04	0.72
S47	0.37	0.61
S48	0.13	0.63
S49	0.25	0.61
S50	−0.25	0.81
S51	0.23	0.68
S53	−0.05	0.72
S54	0.15	0.65
S55	0.11	0.64
S57	0.23	0.65
S59	0.28	0.60
S60	0.27	0.64
S61	0.22	0.62

Note. Communication and S21 are the reference category/participant. SE = standard error.
*$p < .05$.

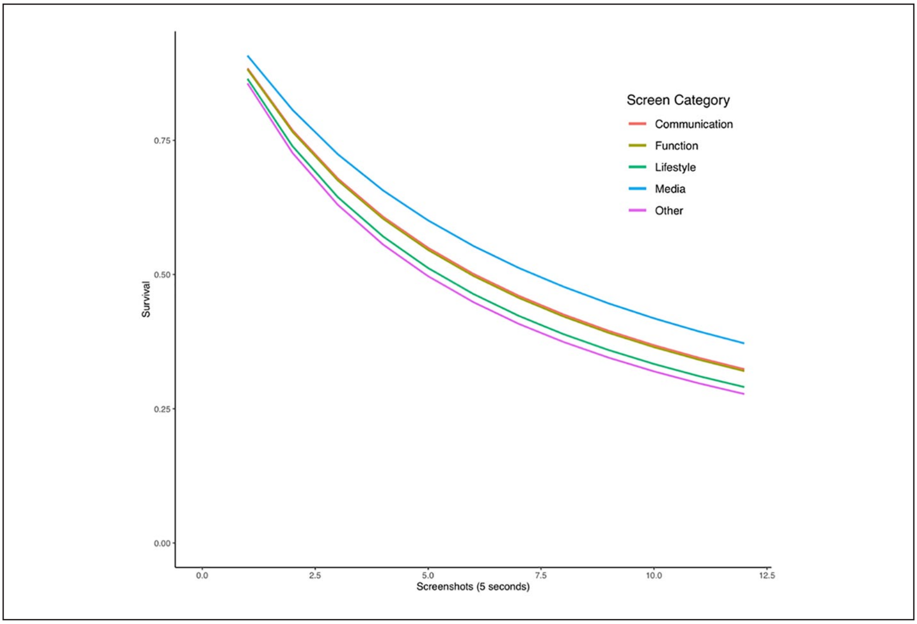

Figure 2. General activity survival analysis results.
Note. Survival analysis with general activity category as a predictor (not stratified by participant for plotting purposes). *News/entertainment (media)* segments had the longest survival times, while *other* segments had the shortest survival times.

remaining in that general activity category (*y*-axis) at a specific time (*x*-axis), with the implied median screen segment survival time located where the curve intersects the 0.50 mark on the *y*-axis.

Exploration of Content "Stickiness" Within General Activity Categories

Within each of the general activity categories (except the catch-all *other* category), we examined differences in screen segment lengths between the more specific content categories to address RQ1. Within the *communication* category, as shown in Panel A of Figure 3, *social media* ($\beta = 0.40$, $SE = 0.04$; 25.27 seconds) segments were significantly longer than *e-mail* screen segments (reference category; $\mu = 1.22$, $SE = 0.08$; 16.94 seconds).

In the *function* category, as shown in Panel B of Figure 3, *study/work* ($\beta = 1.30$, $SE = 0.04$; 32.44 seconds) and *search* ($\beta = 0.24$, $SE = 0.05$; 11.24 seconds) segments were significantly longer than the reference category *navigation* ($\mu = 0.57$, $SE = 0.05$; 8.84 seconds) segments. There were only a small number of *lifestyle* screen segments; thus, the clustering within person was ignored. As shown in Panel C of Figure 3, the screen segment lengths across *exercise* (reference category; $\mu = 1.34$, $SE = 0.24$;

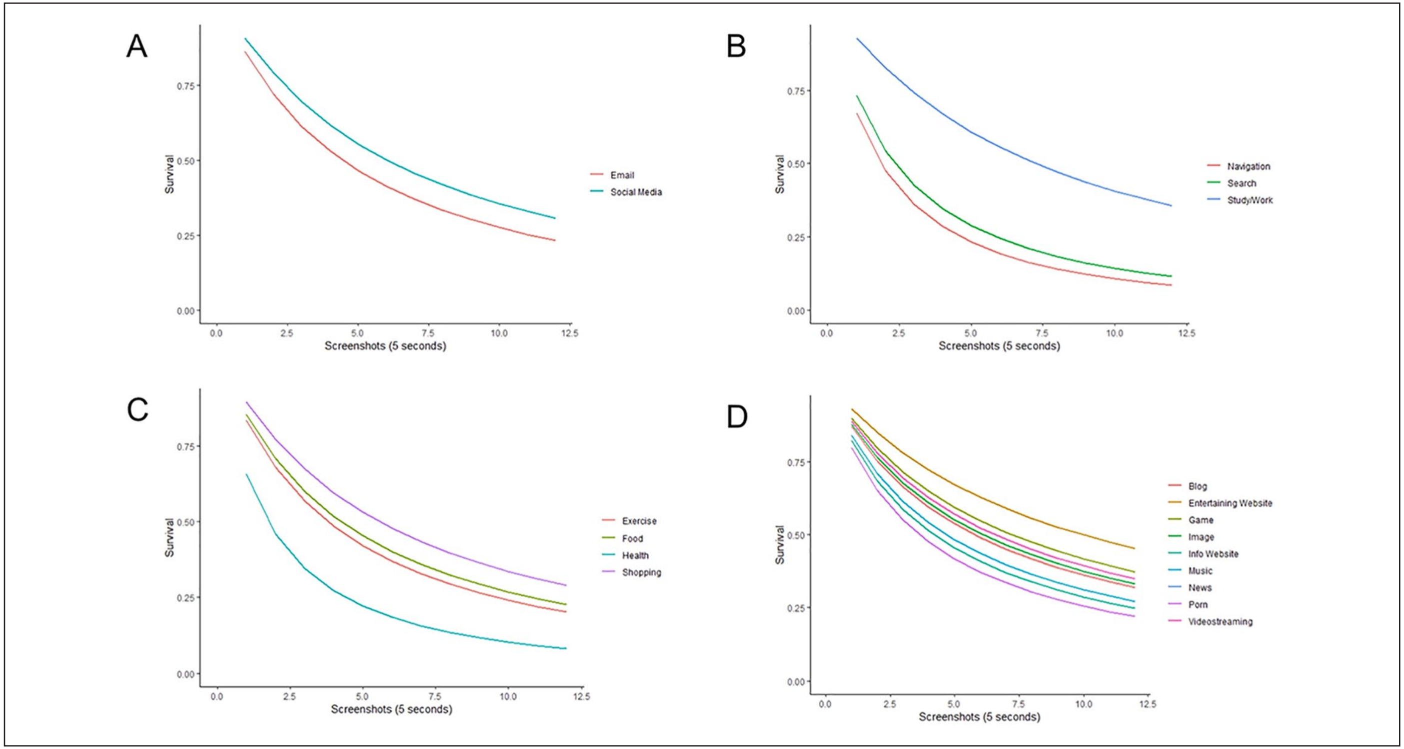

Figure 3. Exploratory survival analyses within each general activity category.

Note. Exploratory survival analyses within each general activity category with content category as a predictor (not stratified by participant for plotting purposes). *Panel A: Communication* survival analysis. Social media segments have a significantly longer survival time than e-mail segments. *Panel B: Function* survival analysis. Study/work and search segments had significantly longer survival times than navigation segments. *Panel C: Lifestyle* survival analysis. No differences in survival time among categories. *Panel D: News/entertainment* survival analysis. Entertaining website segments have the longest survival length within the *news/entertainment* category.

19.10 seconds), *food* (β=0.11, *SE*=0.29; 21.32 seconds), *health* (β =−0.78, *SE*=0.66; 8.75 seconds), and *shopping* (β =0.38, *SE*=0.25; 27.92 seconds) did not significantly differ from each other.

Finally, for the *news/entertainment* survival analysis, *blog* was the reference category (μ =1.83, *SE*=0.14; 31.17 seconds). As shown in Panel D of Figure 3, the specific categories *entertainment website* (β =0.47, *SE*=0.09; 49.87 seconds) and *video streaming* (β =0.13, *SE*=0.06; 35.50 seconds) had significantly longer screen segment lengths than the *blog* category, whereas the specific categories *informational website* (β =−0.25, *SE*=0.07; 24.27 seconds) and *music* (β =−0.20, *SE*=0.09; 25.52 seconds) had significantly shorter screen segment lengths than the *blog* category. *Games* (β =0.28, *SE*=0.89; 41.24 seconds), *image* (β =0.10, *SE*=0.16; 34.45 seconds), *porn* (β =−0.19, *SE*=0.15; 25.78 seconds), and *news* (β =0.06, *SE*=0.07; 33.10 seconds) screen segment lengths did not significantly differ from the *blog* screen segment length.

Discussion

This study used an unobtrusive data collection method—screenomics—to observe the details of participants' laptop use in situ over 4 days to examine (a) whether engagement with screen content on laptops follows a log-normal distribution—evidence of screenertia, and (b) how the "stickiness" of screen segments differs across multiple types of content and inferred media characteristics. Consistent with research examining attentional inertia in other media (e.g., Richards & Anderson, 2004), we found that each individual's laptop screen segment length data was best described by a log-normal survival function. Hypotheses derived from U&G 2.0 about general activity laptop use categories were also supported. *News/entertainment* activities (e.g., entertainment websites, video streaming) that are generally rich in modality had the longest screen segment lengths; that is, this content was the most "sticky" (Sundar & Limperos, 2013) and remained on people's screens for longer, uninterrupted time spans compared to the content of *communication*, *lifestyle*, and *function* activities. Contrary to hypotheses, *lifestyle* activities had the shortest screen segment lengths (excluding *other* activities).

One implication of these results for theorizing about psychological processing of interactive media is that attention is not simply linearly related to the level of interactivity. Our findings suggest that activities lower in interactivity, like watching video clips, tend to draw more sustained screen use than activities higher in interactivity, like communicating via social media, which in turn are higher than *lifestyle* activities (e.g., exercise, food, health) and *function* activities (e.g., navigation, study/work, search). We speculate that media that transports users into a narrative or networking media that promote dialog are important determinants of screenertia, whereas media pertaining to searching and exploring lifestyle-related information tend to be more fleeting. In sum, our findings indicate that rich affordances do not necessarily lead to screenertia (longer segment lengths).

We also explored the survival times of specific content categories within our general activity categories. We found that (1) within *communication* activities, social media use had significantly longer screen segment lengths than e-mail, (2) within *function* activities, study/work had the longest screen segment lengths, (3) within *lifestyle* activities, the screen segment lengths of specific categories (exercise, food, health, shopping) did not significantly differ from each other, and (4) within *news/entertainment* activities, entertainment websites had the longest screen segment lengths. These results also highlight the importance of considering the interactivity, modality, and agency afforded by each kind of content. For example, in the context of communication activities, social media had higher screenertia (longer screen segment lengths) than e-mail, indicating that richness in modality, in addition to the interactivity afforded by the content, plays a role in "stickiness." Alternatively, as in the case of video streaming versus gaming, we discovered that the modality affordance, while providing action possibilities, does not always engender user actions on the screen, but it still results in higher screenertia than other affordances (e.g., interactivity) that engage users in on-screen activities. Our evidence suggests that richer affordances may not always be desirable. In some cases, fewer affordances may signal greater user interest and activity. Future work can more specifically quantify the amount of each affordance embedded in specific media to determine exactly which combinations of affordances drive differences in user engagement.

Reconceptualizing the Dynamics of Media and Attention

Screenertia is one way to describe the *dynamics* of interactive media use—i.e., how users' attention and engagement with media changes over time. Social scientists already draw on the dynamic systems approach—originally developed in the field of physics—to describe similar complex, often non-linear processes (Han & Lang, 2020; Thelen & Smith, 1994; van Geert, 1998). For example, communication researchers have used a dynamic systems approach to examine motivational processing and media multitasking. In this line of work, Wang and colleagues have tested the dynamic nature of media choice and media effects on physiological (e.g., heart rate, skin conductance; Wang et al., 2011), emotional (e.g., positive and negative affect; Xu et al., 2019), and behavioral outcomes (e.g., social media use; Wang et al., 2012). They have employed a variety of methods (e.g., differential equation models, dynamic panel models) to examine feedback loops and reciprocal effects of media characteristics and users. In this study, we used parametric survival models to mathematically describe the stochastic process that generated distributions of screen segment lengths and to examine how the distributions differed across individuals and across different types of media content. Complementing prior work, we demonstrate how dynamic systems concepts and methods can be incorporated into media research to expand our understanding of how people allocate their attention in a complex, interactive modern media environment.

New media require new concepts to describe the dynamics of user behaviors and to understand the underlying mechanisms driving these behaviors. A key component in understanding dynamic behaviors is to observe behavior at the time scale at which it actually manifests. Individuals move through content quickly (in this study, approximately every 20 seconds), creating their own unique threads of experience. Current theories of media behavior need to reflect these dynamic and idiosyncratic behaviors. Three directions may be particularly useful. First, our data suggest that media processing unfolds in short segments, meaning that theories about media should more prominently consider short units of experience. For example, U&G's propositions could focus more on how second-by-second changes in the media experience are related to processing motivations. The vast majority of U&G studies focus on how an entire media product (e.g., sitcom, news bulletin) leads to particular gratifications (e.g., escapism, surveillance), without paying much attention to the many actions and processing decisions that occur during the course of media reception. The granularity afforded by the screenomics approach enables testing of U&G 2.0 hypotheses about the gratifications obtained by a variety of momentary actions (e.g., clicking a link, customizing a setting) that users perform when they use digital media. A better understanding of micro-level media processing as users engage with various media affordances could supplement processing motivations that more typically refer to large units of experience (e.g., how a smartphone might be used over days and weeks) or to large categories of content (e.g., news, social media) that obscure within-category variance and idiosyncratic configurations.

Second, the importance of observing media behaviors from moment to moment extends beyond the study of attention and uses and gratifications. From a broader perspective, it points to the possibility of incorporating screen observations in research to investigate the interplay of content attributes, user characteristics, technology affordances, and situational factors in driving and maintaining users' engagement with media content, thus enriching media theories. For instance, mood management theory recognizes how individuals' moods fluctuate and subsequently affects their selection of media (Zillmann, 1988). A combination of screen observations and ecological momentary assessments can better test the core propositions of mood management theory. Frequent assessments of individuals' moods aligned with screen observations will allow researchers to parse whether individuals select and attend to content that helps them regulate or optimize their mood (or if media content dysregulates or dampens individuals' moods). In this case, screenertia can be used as a measure of media engagement and the result of users' moods. Current theory may lack the specificity needed to develop hypotheses about how these processes occur at fast time scales, but systematic testing of the association between screen content and users' moods will help researchers better understand (a) whether individuals' moods dictate their media choice, (b) the moods that individuals experience during media reception, and (c) the moods that result from individuals' media experience, and the subsequent decay of these moods.

Third, our framework facilitates inductive theory building that has gained new currency across the social sciences in light of recent advances in collecting, processing, and analyzing "big data." Careful mining and analysis of large corpuses of data are aiding the development of new theoretical formulations, with scholars issuing calls to end the "incoherency problem" that often results from retrofitting data about emergent phenomena to outdated theories (cf. Munger et al., 2021). Our analyses contribute to the on going push for descriptive, inductive, and person-specific work that provide much needed groundwork for revising and developing theory for understanding dynamic media behaviors (Beyens et al., 2020; Valkenburg et al., 2021). Future endeavors are needed to more fully explicate, explore, and test new dynamic-systems concepts in the context of contemporary media use behaviors.

Limitations and Future Directions

While our data collection method allowed for the examination of over 566 hours of in situ laptop use and captured content that is not often recorded using URL logging techniques (e.g., working in MS Word, using Finder), some limitations of the method and modeling should be noted. First, screenshots were collected at five-second intervals, which may not be fast enough to capture all the changes in attention that manifest in new media. The technology allows for easy switching among multiple windows and multiple types of content at even faster cadences. Indeed, many of the raw distributions of segment lengths depicted in Figure S2 have many segments at the fastest interval we could observe (5 seconds). When we are able to obtain more continuous streams of screenshots (e.g., every second), we will likely learn even more about how new media environments influence and afford very short bursts of attention.

Second, we assumed that the content captured on participants' laptop screens was the focus of participants' attention. Although we did not assess if participants were looking at their screens, talking with friends while intermittently working on their laptop, or had left their laptop unattended, prior research suggests that the time between changes in screen content approximates users' actual gaze (Holmes et al., 2012; Jensema et al., 2000; Siefert et al., 2008). Analytically, we chose to retain any particularly long segments to ensure consistency in our operationalization of attention (i.e., segment length) and to avoid subjective or uninformed judgments about whether individuals were actually attending to their screen. Future research should, however, consider use of eye-tracking, keystrokes, and mouse movements to better discern where individuals are directing their attention.

Third, in our survival models, we examined how content of the screen was related to screen segment length. However, our models were limited in that they did not allow for individual differences in how screen content moderates "stickiness" and did not consider the content of the prior screen(s)—for example, whether and when stickiness is primed and/or attenuated by the preceding content. Previous research has shown that sustained attention with prior content is correlated with a greater length of attention after the content has switched (Anderson & Lorch, 1983 with children watching Sesame Street; Burns & Anderson, 1993 with adults and primetime/commercials). Furthermore, although we allowed for between-person differences in the location and scale parameters of the survival models, we did not examine what user characteristics might drive these differences. Future studies could additionally make use of analytical models that include temporally lagged media characteristics (i.e., information about the prior screen) and individual-level user characteristics.

Fourth, our coding scheme for screenshots was based on the content present on the screen and the affordances often associated with particular types of content (e.g., gaming being high in agency and interactivity). For example, following from U&G 2.0, we prioritized source interactivity (i.e., the user as the source of information) as a key component of social media and the *communication* content category. Other aspects of screen content may also be useful when considering how media influences attention. Social media might instead operate as a form of *news/entertainment* that spans multiple information modalities (e.g., text, photos, videos). Furthermore, while our coding scheme was designed with mutually exclusive categories, it may also be useful to consider whether a given activity falls within multiple categories (e.g., looking at news on Facebook vs. responding to a post on Facebook) to better capture the nuances in affordances of screen activities.

Finally, our sample consisted of screens from 30 undergraduates studying at one university during one semester. The sample is not representative of the general population in age and race, and while probably indicative of the media environment students were engaged with in 2013, may not necessarily apply to the current media environment. For example, some of the websites visited by participants no longer exist while new websites have been created and gained popularity since the data were collected (e.g., heavily visual social media, like Instagram and TikTok, have increased in popularity). Furthermore, the technology itself is continually changing (e.g., faster and more ubiquitous internet, more powerful smartphones). Although our examination of only one screen (i.e., laptops) limits the generalizability of our findings, our approach provides a foundation for future research by extending the attentional inertia phenomenon from passive media behaviors (e.g., television watching) to interactive media behaviors (e.g., engagement with laptops, smartphones). Given that the media environment is dynamic and evolving, newer samples are needed to track how the ongoing evolution of media influences attention.

Conclusion

This study introduced a new concept, screenertia, and provided an explication and empirical articulation in the form of the log-normal distribution using screen captures collected in situ. Screenertia can offer insights for differential media effects—why some content on some screens has stronger effects—and pave the way for a richer understanding of media effects based not simply on the type of media content but on the affordances associated with the reception of that content. As we have shown, content that differs in interactivity, modality, and agency predict variations in screenertia. Future studies could examine screenertia as a direct predictor of media effects or identify the optimal combinations of media content and interface affordances that predict screenertia. Explorations of both the causes and effects of screenertia will enhance our understanding of the dynamics of user engagement with a variety of interactive media that have screen display. Historically, media-effects research has focused on content genres and medium features as causal factors without rigorously probing the extent to which users engage with the content or the medium. Our framework provides a solution by modeling users' behavioral engagement, which can be quite important for understanding how and when media influences individuals' psychological processes and behavior. In practical terms, metrics related to screenertia provide a new level of precision in measurement of online audiences by capturing survival times of specific content and interface elements, thereby providing valuable input for advertisers and marketers as well as guiding algorithms for accurately personalizing media offerings at the individual user level.

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Supplemental Material

Supplemental material for this article is available online.

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