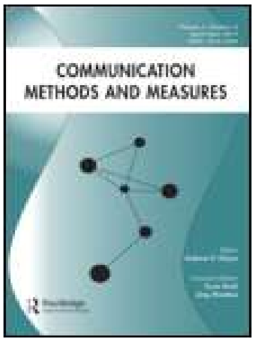

Communication Methods and Measures

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/hcms20

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COMMUNICATION METHODS AND MEASURES
https://doi.org/10.1080/19312458.2020.1812556

From Filled to Empty Time Intervals: Quantifying Online Behaviors with Digital Traces

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ABSTRACT

Ordinary users fill some intervals on the time continuum by engaging in an online behavior and leave other intervals empty by disengaging from the behavior. Existing time-based measurements of online behaviors exclusively focus on characterizing filled time intervals and completely ignore the information embedded in empty time intervals. Empty time intervals, referring to time gaps between consecutive behaviors, carry important information on how time is organized for online behaviors. By analyzing two behavioral log files on webpage browsing and mobile application use, the study evaluates whether online behaviors characterized by empty time intervals differ from or accord with online behaviors characterized by filled time intervals. Behavioral burstiness, which measures the distribution of empty time intervals in consecutive online behaviors, is found to unveil behavioral patterns that are distinct from temporal duration that measures the overall length of the filled time intervals of online behaviors. Temporal duration is much more extended in mobile use compared with web surfing, whereas behavioral burstiness in mobile use is lower than that in web surfing. Marked circadian rhythms are observed in behavioral burstiness in web surfing and mobile use, whereas circadian rhythms are vague in temporal duration in web surfing and mobile use.

Time, as the common denominator of all human behaviors, has been an indispensable element in the empirical operationalization of online behaviors. Self-reported time-based measurements have been widely employed to quantify users' online behaviors in communication research (e.g., Blank, 2017; Kruikemeier et al., 2014; Livingstone & Helsper, 2010; Zhu & He, 2002). With enhanced awareness of biases and limitations in self-reported measures (Fishbein & Hornik, 2008; Prior, 2009) and increasing availability of other viable data sources (Van Atteveldt & Peng, 2018), the past decade has witnessed a burgeoning interest in quantifying online behaviors with user-generated digital traces in communication research and beyond (e.g., Taneja et al., 2012; Zhang et al., 2017). Online behaviors captured in digital traces are consistently found to be more accurate than those in self-reported measures (e.g., Araujo et al., 2017; Boase & Ling, 2013; Scharkow, 2016). In spite of the improved

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measurement quality of online behaviors, the conceptual underpinning of online behaviors in digital traces in most empirical studies is inherited from that of self-reported measures, both of which are built upon the time-budget paradigm (Adam, 1990).

The time-budget paradigm conceptualizes time "as a resource being expressed by numerical specification of both the duration and the frequency with which activities were carried out" (Adam, 1990, p. 95). The core concern in the time-budget paradigm is how ordinary users allocate their limited time resources to various behaviors or activities. To unravel the time allocation pattern, individuals' behaviors are projected to a continuous-time continuum, which decomposes the continuous-time continuum into intervals of specific length. Some intervals on the time continuum are *filled* by particular types of online behaviors, whereas other intervals are *empty* over which a behavior of interest is not observed (Zaheer et al., 1999). This projection process is illustrated in Figure 1 where the vertical dimension represents specific online behaviors and the horizontal dimension represents the 24-h time continuum. Empirical studies with both self-reported measures and digital traces have exclusively capitalized on the filled time intervals to quantify online behaviors, whereas the information embedded in empty time intervals are largely ignored. The filled time intervals are aggregated along the horizontal or/and vertical dimension in Figure 1 into the time-based measurements of online behaviors, such as the duration (Araujo et al., 2017; Cotten et al., 2011), frequency (Boase & Ling, 2013; Jung & Sundar, 2018), and diversity (Peng & Zhu, 2011; Zhang et al., 2017) of online behaviors in a certain time window (e.g., day, week, or month).

With the increasing integration of social and mobile media in our daily lives, more and more intervals on the time continuum may be filled by online behaviors. When the intervals filled by a specific online behavior reach a saturation stage, the sole focus on the filled intervals is not adequate to comprehensively reveal patterns and differences on online behaviors of ordinary users. As illustrated in Figure 1, the three users differ slightly on their duration of online news consumption ranging from 35 min to 61 min in a day, whereas they differ remarkably on the distribution of empty intervals between consecutive news consumption behaviors. The online news consumption of

ID	Communication	Entertainment	News	Search	SNS	Daily Total (Unit: Minutes)
User_1	36	43	48	48	58	233
User_2	46	34	35	65	44	224
User_3	39	38	61	38	32	208

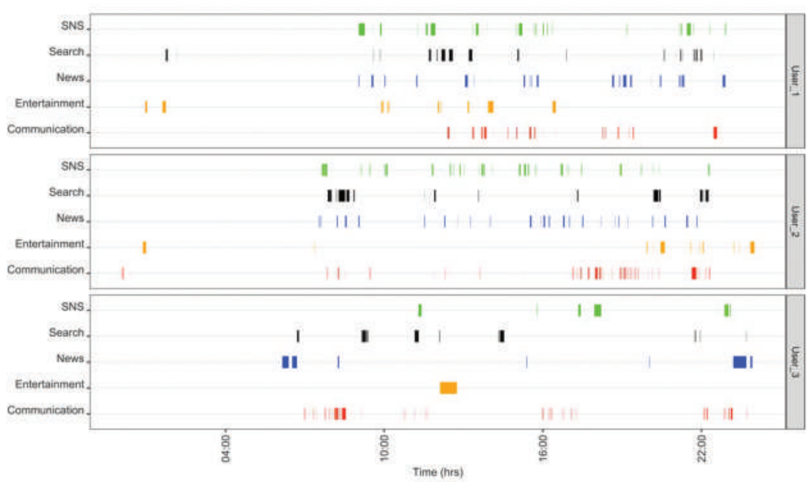

Figure 1. Projection of online behaviors to a time continuum.

User 1 and User 2 is separated by relatively short empty intervals between two consecutive behaviors, whereas that of User 3 is amassed together with longer empty intervals between. The displayed differences on empty time intervals among three users in Figure 1 are concealed in existing measures of online behaviors characterized by filled time intervals.

As existing measures of online behaviors may be inadequate or outdated, a refreshed perspective in the conceptual explication and empirical operationalization of online behaviors is of theoretical and methodological necessity in communication research (Domahidi, 2018). The empty time intervals on the time continuum have the potential to provide a distinct and complementary perspective in quantifying online behaviors. By employing two large-scale log file datasets which track individuals' webpage browsing behavior and mobile application use among two independent panels of users in Hong Kong, the study will make one of the first attempts in communication research to empirically assess if online behaviors characterized by empty time intervals differ from or accord with online behaviors characterized by filled time intervals.

Empty Time Intervals: Empirical Findings, Theoretical Implications and Research Questions

Empty time intervals between two consecutive behaviors, which consider time order and intervals among behaviors, carry important information on how time is organized for the online behaviors of ordinary users as owners of their time (Peng & Zhu, 2020). It is equally, if not more, important to understand the patterns underlying the organization of time in various online behaviors as to understand the patterns underlying the allocation of time in various online behaviors. For example, how regular is the online communication of ordinary users? Will news consumption or information-seeking be clustered into short and separate segments of time or will they be evenly spread over time? The empty time intervals on a time continuum, which is extremely difficult to observe in self-reported measures, have become a built-in element in time-stamped digital traces. We will first review what has been found about empty time intervals in empirical studies and discuss the theoretical implications of empty time intervals in communication research. Then, we will propose three research questions to empirically assess empty time intervals as a measurement of online behaviors.

What Has Been Found about Empty Time Intervals?

Owing to the lack of appropriate empirical data during the pre-electronic age, human behaviors are widely assumed to be uniform in time (Barabási, 2005; Gross & Harris, 1985), which can be generally described in statistical terms as a homogeneous Poisson process (Haight, 1967). In this case, the empty time intervals between two consecutive behaviors, which is conceptualized in human dynamics research as interevent time (Barabási, 2005), follow an exponential distribution. However, the temporal homogeneity assumption of human behavior is too strong to be true in actual settings. The increasing availability of time-stamped digital traces has facilitated the empirical testing of the homogeneity assumption and triggered the interest of researchers from different disciplines to uncover the patterns underlying empty time intervals in a wide array of online behaviors.

By analyzing empty time intervals derived from the e-mail communication records of thousands of users, Barabási (2005) is among the first to argue that human behaviors are highly heterogeneous in time. Specifically, human behaviors display a bursty pattern, thereby showing enhanced activity levels within short periods of time followed by long empty time intervals. The bursty pattern has been observed in a variety of interactive and noninteractive online behaviors, such as social networking (Grabowski & Kosinski, 2008; Ubaldi et al., 2017), knowledge sharing (Yan et al., 2017), mobile phone calls (Candia et al., 2008; Gonzalez et al., 2008), webpage browsing (Geczy et al., 2008; Goncalves & Ramasco, 2008), online gaming (Grabowski & Kruszewska, 2007), videoon-demand watching (Crane & Sornette, 2008), and tweeting (Murthy et al., 2016; Ross & Jones, 2015).

What Do Empty Time Intervals Imply in Communication Research?

Moving from filled to empty time intervals enables the empirical detection of bursty patterns in online behaviors, which has methodological and theoretical implications in media use studies and media effect research. First, it sheds light on how ordinary users schedule their online behaviors, which can advance our knowledge on the time heterogeneity of communicative behaviors. When the available time resources and frequency of a specific behavior are controlled, high burstiness implies that individuals' time for a certain behavior is less interrupted by other competing behaviors. Conversely, low burstiness implies that individuals' time for a certain behavior is regularly interrupted by other competing behaviors. Consequentially, high burstiness in human communication can improve team performance (Riedl & Woolley, 2017) and enhance collaborative knowledge production (Zheng et al., 2019).

As the empty time intervals between two consecutive behaviors provide windows of opportunities for ordinary users to engage with other behaviors, it can be employed to explicate the concept of audience availability which is an important situational predictor of media use (Webster & Wakshlag, 1982). The length of empty time intervals refers to the amount of time available for ordinary users to engage with other behaviors, which is a popular measurement of audience availability in existing studies (Nelson & Taneja, 2018; Taneja & Viswanathan, 2014). The bursty pattern underlying the empty time intervals conveys additional information about how the available time resources are structured temporally, which will provide an additional dimension to explicate audience availability.

Thirdly, the bursty levels of communicative and information behaviors can be employed to reverse engineer the information load to be tackled by ordinary users in certain timespans (Rodriguez et al., 2014). In a highly bursty session of news consumption and/or information seeking, users will acquire an overwhelming amount of information at a considerable rate (Riedl & Woolley, 2017), which will demand long periods of time and additional cognitive resources to process. Information acquired in a highly bursty session of behaviors will produce weaker memories than information acquired in a less bursty session of behaviors, which is known in psychological research as the spacing effect (Smith & Scarf, 2017). The rate at which users acquire information influences their information processing behavior, including how they prioritize information from different sources, how much information they process, and how quickly they process information (Rodriguez et al., 2014). Moreover, users' susceptibility to social contagions is substantially contingent upon the rate at which they receive information (Rodriguez et al., 2014).

Fourthly, individuals' efforts to inhibit bursty behavior and switch to long periods of inactivity for certain behaviors require the expenditure of self-control strength, which is the "inner, limited resource that is depleted afterward" (Muraven & Baumeister, 2000, p. 247). The greater the level of burstiness of a behavior, the more the self-control strength needed to stop the behavior. Such an inhibition behavior can lead to an ego depletion that renders individuals temporarily less able and willing to function normally or optimally (Baumeister & Vohs, 2007). When an individual is cognitively depleted, he/she fails to make progress on a task. Moreover, cognitively depleted individuals will miss or ignore numerous details in consuming content on social media (Kooti, 2016). Such ego depletion effects have been found in multitasking behaviors and mobile phone use (Lanaj et al., 2014).

What to Be Done with Empty Time Intervals in the Current Study?

The empty time intervals offer an alternative and viable perspective on quantifying online behaviors, whereas the fine-grained timestamps in digital traces make it possible to directly estimate such empty time intervals. Although empirical evidence have been accumulated that empty time intervals can reveal the bursty pattern of online behaviors, it is methodologically desirable and necessary to carefully evaluate and compare online behaviors characterized by empty intervals with traditional measures of online behaviors in communication research. Previous empirical assessments of measures of online behaviors (e.g., Araujo et al., 2017; Boase & Ling, 2013; Scharkow, 2016) focused on the between-subject differences on under-reporting or over-reporting of online behaviors in self-reported measures and digital traces. Different from previous studies, the current study evaluates two measures of online behaviors derived from digital traces by taking into account within-subject variations and between-subject differences. Given the methodological and exploratory nature of the current study, we do not impose any theoretically driven hypothesis. Instead, our assessment is organized around the following three questions.

In the past decade, the media landscape has witnessed drastic changes characterized by the rise of social and mobile media, the empowerment of ordinary users, and the increasing integration of technological elements in information production, seeking and sharing. The rapidly changing media landscape and information environment have considerably influenced how ordinary users will allocate and organize their time for different types of online behaviors. Users' online behaviors are expected to change as an adaption to the development of media landscape, which is conceptualized as the appropriation of information and communication technologies (ICTs). The appropriation of ICTs refers to "an active and creative process that ends in various usage patterns on both individual and society level" (Wirth et al., 2008, p. 598). Empirical studies have been conducted to examine how users will behave differently on mobile platforms and non-mobile platforms. Twitter users on mobile platforms are more active, share less links and post more location-specific contents than those on non-mobile platforms (Perreault & Ruths, 2011). Social media posts delivered from mobile devices are more ego-centric, conversational and negative than those delivered from web-based platforms (Murthy et al., 2015). However, very little is known about how time allocation and organization for various online behaviors are changed when users migrate from the browser-based web on home computers to the "always-on, always-on-you" (Turkle, 2008) mobile Internet. The first research question in our empirical assessment is:

RQ1: How will online behaviors characterized by filled and empty time intervals change as a response to macrolevel technological development from browser-based web to mobile Internet?

Individuals' online behaviors are contextualized in their routine management of public and private affairs on daily and weekly cycles. To satisfy their biological, social, and information needs at different timespans, each individual is expected to possess certain intra-individual variations in their online behaviors as a response to the temporal structure they create and own. When individuals retrieve themselves from a highly accessible status during a public time to a relatively disconnected status during a private time (Zerubavel, 1979), their online behaviors are expected to change correspondingly. With the increasing availability and accessibility of digital traces, empirical studies have revealed daily (e.g., Golder & Macy, 2011; Grinberg et al., 2013), weekly (Golder et al., 2007), and seasonal (Golder & Macy, 2011) patterns of online behaviors. These temporal patterns detected at different granularity levels imply ordinary users can routinize their online behaviors (Webster, 2009), which act as an important mechanism through which media use can structure everyday life (Schnauber-Stockmann & Mangold, 2020).

The current study will assess if online behaviors characterized by filled and empty time intervals change in the same manner as a response to the unfolding of clock and calendar time. The change of online behavior that follows a daily cycle is known as circadian rhythms of online behaviors, while the change of online behaviors that follows a weekly cycle is known as the weekly patterns of online behaviors. Therefore, the second research question in our empirical assessment is:

RQ2: Will online behaviors characteristics by filled time intervals and empty time intervals display consistent or discrepant circadian rhythm and weekly pattern?

It has been well established in both theoretical literature and empirical studies that individuals' online behaviors are associated with their socio-demographic characteristics (Scharkow, 2016). Users in different social groups are found to differ in their online behaviors observed in both self-reported measures and digital traces, although the differences vary between self-reported measures and digital traces (Boase & Ling, 2013; Jürgens et al., 2020; Scharkow, 2016). The current study will assess how users from different social groups differ in online behaviors characterized by filled and empty time intervals, respectively. The third research question in our empirical assessment is:

RQ3. How will online behaviors characterized by filled and empty time intervals be associated with between-individual characteristics (i.e., age, gender, education level, and occupation), respectively?

Research Method

The current study employs two client log file datasets collected from two distinct panels of users randomly sampled in Hong Kong. The first dataset, which is called the webpage browsing dataset (WBD), records the webpage browsing behaviors of the panelists at home in four-week spreads in 2002–2003 and 2003–2004. In 2002–2004, webpage browsing via fixed broadband connections was the most popular way to surf the web in Hong Kong and beyond (ITU, 2006). The second dataset, which is called the mobile use dataset (MUD), records the mobile application use of the panelists for 5 months, from July to November 2016. In 2016, mobile Internet became integrated into the daily lives of the general public in Hong Kong, where 98% of all Internet users go online via mobile devices (ITU, 2018). The two panels in WBD and MUD are independent from one another, both of which were recruited by a marketing research firm for local media organizations in Hong Kong. The panelists in WBD and MUD are representative of the online population in Hong Kong in respective time period (i.e., 2002–2004 and 2016). The representativeness of the panels in WBD and MUD is maintained by controlling the gender and age distribution of the panelists, respectively.

Tracking Methods in WBD and MUD

In the WBD, a webpage browsing session is recorded as start when an URL is requested in the webpage browser and the requested URL is fully loaded and displayed on the browser. The webpage browsing session will be considered as active when the webpage is being displayed on the browser. While a user may open multiple browser sessions simultaneously, those sessions which are not on display will not be considered as active. Thus, there are no concurrent browsing sessions recorded in the WBD. A webpage browsing session will be recorded as complete when one of the three conditions is met: (1) the browser is closed; (2) a new URL is requested; (3) the webpage is not on display anymore. Moreover, if a user stays on a webpage browsing session for 30 min without any further actions (i.e., closing the browser, requesting a new URL), the session will be automatically recorded as complete in the WBD. In other words, the longest duration of a webpage browsing session in the WBD will not last longer than 30 min. This 30-min threshold in the WBD may be relatively short from today's perspective. However, it is a reasonable threshold in Hong Kong in early 2000s when the average online time at home is about 350 min per week (Zhu & He, 2002). Thus, a 30-min browsing session in a day accounts for a substantial proportion (60%) of daily online time at home for ordinary Internet users in Hong Kong during the study period.

In the MUD, an on-device meter solution is adopted to track the use of mobile apps on individual mobile devices. Only the active screen engagement is recorded as an app use in the dataset. All apps running in the background are filtered out by the on-device meter. In other words, if an app is active on screen for 3 min and keeps running in the background for another 50 min, the total duration of this app use is recorded as 3 min in the dataset. Moreover, a threshold of 5 consecutive seconds is applied for all app use. If an app use is shorter than 5 consecutive seconds, it will not be recorded in the MUD. This threshold is applied to prevent some behaviors from being identified when they persist for a very short duration, as fast activity changes are assumed not to represent normal usage patterns in the study.

Measurements

In both WBD and MUD, each record consists of four variables: (1) user ID, (2) the starting time of a webpage request in the WBD or application use in the MUD, (3) the end time of the webpage request in the WBD or application use in the MUD, and (4) the requested URL in the WBD or the application category in the MUD. This study focuses on webpage browsing and mobile application usage behaviors in five thematic types, namely, communication, entertainment, news consumption (labeled "News"), information search (labeled "Search"), and social networking site use (labeled "SNS"). The thematic types of the browsed webpages are determined by analyzing the information included in the requested URLs, whereas the thematic types of the mobile applications are determined based on Google mobile application categories. The technical details of the URL analysis to extract the themes of browsed webpages are available in the supplementary material.

Filled time intervals are calculated as the elapsed time between the starting and ending times of a behavior. Temporal duration, which is a popular measurement of media use in communication research, is adopted to characterize the filled time intervals of a specific behavior. Temporal duration of online behaviors refers to the summation of the lengths of all the filled time intervals of a specific behavior in a certain timespan.

Empty time intervals are calculated as the elapsed time between the ending time of a previous behavior and the starting time of the next behavior. Behavioral burstiness (Goh & Barabási, 2008; Min & Goh, 2013) is adopted to characterize the empty time intervals associated with a behavior in a certain timespan. Behavioral burstiness captures the distribution of empty time intervals between two consecutive behaviors and is defined as follows:

$$\mathrm{B} = \frac{\sigma - \langle\tau\rangle}{\sigma + \langle\tau\rangle}$$

where σ and τ are the standard deviation and mean values of a series of empty time intervals, respectively. The value of B ranges from − 1 to 1. The greatest burst level signal is denoted as $\mathrm{B} = 1$, and a neutral sequence is denoted as $\mathrm{B} = 0$. When $\mathrm{B} = -1$, the corresponding series of behaviors is a completely regular (periodic) series. When B is positive, the standard deviation σ is greater than the mean value τ, that is, the series has a higher burst level when B is close to unity. By contrast, when B is close to −1, the series becomes regular.

The WBD and MUD are combined into one dataset to assess and compare behavioral burstiness and temporal duration between web surfing and mobile use. Macrolevel technological development is operationalized as a binary variable, with 0 representing web surfing behaviors captured in the WBD and 1 representing mobile use behaviors captured in the MUD. To examine the circadian rhythm of online behaviors, the 24-h clock time cycle is divided into three timespans, that is, private time from 0 to 7, when individuals can largely embed themselves in their private affairs; public time from 8 to 15 in a day; and hybrid time from 16 to 23 in a day during which individuals in Hong Kong start to withdraw from daily work routines and embed themselves in leisure and private activities. Meanwhile, to examine the weekly pattern of online behaviors, calendar time is measured as a nominal variable with seven categories, that is, from Sunday to Saturday, by extracting weekdays from the starting time of webpage browsing or mobile application use.

In both datasets, demographic characteristics of the panelists, including age, gender, education, and occupation, are collected via online surveys. This study focuses on panelists whose age is between 18 and 64 years in both WBD and MUD, thereby leading to a sample of 2,454 users in the WBD and a sample of 2,363 users in the MUD. The panelists' mean age is 30 years (*SD* = 11) in the WBD and 34 years (*SD* = 11) in the MUD. In the WBD, 57% of the panelists are male and 43% are female, whereas in the MUD, 52% are male and 48% are female. Education level and occupation are coded into common scales in both datasets. Education level is operationalized as an ordinal variable with three categories, that is, low, medium, and high. Occupation is operationalized as a nominal variable with four categories, namely, full-time students, service workers, professionals and managers, and unemployed (including jobless individuals, retired individuals, housewives, and others).

Analytical Design

As observations are nested with panelists in both WBD and MUD, linear mixed modeling (LMM) is employed to uncover within-individual variations and between-individual differences in behavioral burstiness and temporal duration, respectively. Specifically, two LMM models are estimated, that is, an unconditional mean model and a random-intercept model. The unconditional mean model is estimated without explanatory variables included. Significant between-individual variations are found in behavioral burstiness and temporal duration, as indicated by a significant intercept variance ($\tau_{00} = 0.017, p < 0.001$ for behavioral burstiness and $\tau_{00} = 0.13, p < 0.001$ for temporal duration). The intraclass correlation coefficient (ICC) is calculated to determine the proportion of total variance in behavioral burstiness and temporal duration that lies systematically among individuals. The ICC is equal to 0.34 for behavioral burstiness and 0.36 for temporal duration. This high ICC suggests that LMM performs better than traditional methods in estimating fixed effects (De Leeuw & Kreft, 1995). Next, a random-intercept model is estimated to examine within-individual variations and between-individual differences in behavioral burstiness and temporal duration, respectively.

Analytical Findings

The analytical findings are organized as follows: First, descriptive statistics on empty and filled time intervals and on behavioral burstiness and temporal duration are reported. Second, to answer the proposed research questions, analytical results from the random-intercept model are presented, including (1) differences in behavioral burstiness and temporal duration between platforms (i.e., web surfing vs mobile use) and across different types of online behaviors, (2) circadian rhythms and weekly patterns in behavioral burstiness and temporal duration, and (3) between-individual differences in behavioral burstiness and temporal durations.

Descriptive Statistics

The empty and filled time intervals of the five behaviors in web surfing and mobile use follow a fat-tailed distribution. Table 1 reports the summary statistics of the empty and filled time intervals of the five types of behaviors in web surfing and mobile use. The median length of the empty intervals of the five behaviors in web surfing ranges from 2 s to 7 s, whereas the median length of the empty intervals of the five behaviors in mobile use ranges from 76 s to 230 s. The median length of the filled intervals of the five behaviors in web surfing ranges from 6 s to 9 s, whereas the median length of the filled intervals of the five behaviors in mobile use ranges from 29 s to 47 s.

Behavioral burstiness is moderately correlated with log-transformed temporal duration. As shown in Table 2, the zero-order Pearson correlation between the behavioral burstiness and log-transformed temporal duration of the five behaviors ranges from 0.41 to 0.53 in web surfing and from 0.19 to 0.40 in mobile use. The moderate bivariate correlations suggest that behavioral burstiness and temporal duration convey distinct information on online behaviors.

Table 1. Summary statistics of empty and filled time intervals.

Empty Time Intervals						
	Web Surfing (units: seconds)			Mobile Use (units: seconds)		
Behavioral Types	Mean	Median	*SD*	Mean	Median	*SD*
Communication	615	3	3,622	2,241	209	5,892
Entertainment	399	2	2,849	2,908	76	7,495
News	978	5	4,398	3,818	110	8,423
Search	846	7	4,182	2,906	146	7,077
SNS	404	2	2,884	2,522	230	6,274
Filled Time Intervals						
Behavioral Types	Web Surfing (units: seconds)			Mobile Use (units: seconds)		
	Mean	Median	*SD*	Mean	Median	*SD*
Communication	24	6	91	91	29	270
Entertainment	27	6	90	191	37	489
News	32	9	92	164	35	403
Search	19	7	67	133	41	317
SNS	20	6	68	128	47	266

Table 2. Zero-order pearson correlation between behavioral burstiness and temporal duration.

	Correlation between Behavioral Burstiness and Temporal Duration (Original Score)		Correlation between Behavioral Burstiness and Temporal Duration (Log Transformed)	
Behavioral Types	Web Surfing	Mobile Use	Web Surfing	Mobile Use
Communication	0.34	0.30	0.48	0.40
Entertainment	0.35	0.18	0.48	0.27
News	0.32	0.13	0.53	0.19
Search	0.28	0.25	0.41	0.33
SNS	0.39	0.32	0.52	0.38

All correlation coefficients are statistically significant at the 95% confidence level.

Differences in Behavioral Burstiness and Temporal Duration across Platforms and Behavioral Types

The conditional R^2 of the random-intercept model is 0.33 for behavioral burstiness and 0.47 for temporal duration. The model fit of the random-intercept model is significantly better than that of the unconditional mean model for behavioral burstiness and temporal duration. The main-effect estimates of the random-intercept model for behavioral estimates and temporal duration are summarized in Table 3.

Temporal duration in web surfing (estimated mean = 2.23, 95% CI [2.21, 2.26]) is significantly shorter than that in mobile use (estimated mean = 2.66, 95% CI [2.10, 3.22]). In addition, behavioral burstiness in web surfing (estimated mean = 0.489, 95% CI [0.486, 0.493]) is significantly greater than that in mobile use (estimated mean = 0.248, 95% CI [0.245, 0.250]). Post-hoc Tukey tests are conducted to make pairwise comparisons between behavioral burstiness and temporal duration across platforms and behavioral types. The statistical significance testing of the pairwise comparisons and estimated marginal means of behavioral burstiness and temporal duration are reported in Figure 2.

Two noticeable differences between behavioral burstiness and temporal duration have emerged from the pairwise comparisons. First, the behavioral burstiness of communication (estimated mean = 0.515, 95% CI [0.511, 0.519]) in web surfing is significantly greater than that of the other four behaviors, whereas the temporal duration of communication (estimated mean = 2.26, 95% CI [2.23, 2.28]) in web surfing is only significantly longer than that of search (estimated mean = 2.13, 95% CI [2.05, 2.22]). Second, the behavioral burstiness of communication (estimated mean = 0.241, 95% CI [0.238, 0.244]) in mobile use is significantly lower than that of entertainment (estimated mean = 0.262, 95% CI [0.259, 0.265]) and search (estimated mean = 0.260, 95% CI [0.257, 0.263]) but significantly greater than that of

Table 3. LMM estimates of behavioral burstiness and temporal duration.

	Behavioral Burstiness [a]		Temporal Duration [a,b]	
	Estimates	95% CI	Estimates	95% CI
Intercept	0.435***	[0.416, 0.453]	1.906***	[1.853, 1.959]
Platform and Behavioral Types				
Platform (Web Surfing = 0, Mobile Use = 1)	−0.173***	[−0.195, −0.151]	0.810***	[0.743, 0.878]
Behavioral Type 1 (Communication = 0, Entertainment = 1)	0.034***	[0.014, 0.055]	0.191***	[0.141, 0.241]
Behavioral Type 2 (Communication = 0, News = 1)	−0.021**	[−0.039, −0.003]	0.170***	[0.126, 0.214]
Behavioral Type 3 (Communication = 0, Search = 1)	0.011	[−0.02, 0.042]	−0.042	[−0.118, 0.034]
Behavioral Type 4 (Communication = 0, SNS = 1)	0.056***	[0.03, 0.082]	0.120***	[0.055, 0.184]
Weekly Patterns and Circadian Rhythms				
Weekday 1 (Sunday = 0, Monday = 1)	0.007	[−0.003, 0.018]	0.028*	[0.003, 0.054]
Weekday 2 (Sunday = 0, Tuesday = 1)	−0.005	[−0.016, 0.006]	0.031**	[0.005, 0.057]
Weekday 3 (Sunday = 0, Wednesday = 1)	0.007	[−0.004, 0.017]	0.043***	[0.017, 0.069]
Weekday 4 (Sunday = 0, Thursday = 1)	0.012**	[0.002, 0.023]	0.035**	[0.009, 0.061]
Weekday 5 (Sunday = 0, Friday = 1)	0.012*	[0.001, 0.023]	0.032**	[0.006, 0.058]
Weekday 6 (Sunday = 0, Saturday = 1)	0.006	[−0.005, 0.016]	0.009	[−0.017, 0.035]
Daily Interval 1 (Public Time = 0, Hybrid Time = 1)	−0.018**	[−0.034, −0.003]	0.071***	[0.033, 0.11]
Daily Interval 2 (Public Time = 0, Private Time = 1)	−0.045***	[−0.062, −0.028]	0.004	[−0.038, 0.045]
Demographic Variables				
Sex (Male = 0, Female = 1)	0.020***	[0.011, 0.03]	0.092***	[0.065, 0.119]
Age	−0.001***	[−0.001, 0]	0.003***	[0.001, 0.005]
Education Level 1 (Low = 0, Medium = 1)	0.021***	[0.01, 0.032]	0.044**	[0.011, 0.077]
Education Level 2 (Low = 0, High = 1)	0.035***	[0.022, 0.048]	0.070***	[0.03, 0.109]
Occupation 1 (Students = 0, Unemployed = 1)	−0.020**	[−0.034, −0.005]	−0.001	[−0.044, 0.043]
Occupation 2 (Students = 0, Service Workers = 1)	−0.007	[−0.02, 0.005]	−0.034	[−0.072, 0.004]
Occupation 3 (Students = 0, Professionals = 1)	−0.017**	[−0.032, −0.003]	−0.017	[−0.061, 0.027]
Control Variable				
Frequency of Behavior	0.004***	[0.004, 0.004]	0.012***	[0.012, 0.012]
Random Effects				
σ^2	0.03		0.17	
τ_{00}	0.003		0.05	
ICC	0.08		0.22	
Model Summary				
Number of Users	4,817		4,817	
Number of Observations	386,736		386,736	
Marginal R^2/Conditional R^2	0.27/0.33		0.32/0.47	

* $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$
a. Only main-effect estimates are reported in the table, whereas interaction effects estimates can be found in the supplementary material. b. The dependent variable is log-transformed.

SNS (estimated mean = 0.237, 95% CI [0.234, 0.240]). Nevertheless, the temporal duration of communication (estimated mean = 2.75, 95% CI [2.24, 3.27]) in mobile use is significantly shorter than that of news (estimated mean = 2.94, 95% CI [2.42, 3.45]) and SNS (estimated mean = 3.06, 95% CI [2.523, 3.59]) but significantly longer than that of search (estimated mean = 2.69, 95% CI [2.18, 3.21]).

Within-individual Variations in Behavioral Burstiness and Temporal Duration

No consistent and marked weekday differences are observed in behavioral burstiness and temporal durations according to the post hoc Tukey pairwise comparison tests. The statistical significance testing of the pairwise comparisons is summarized in Figure 3. No significant weekday differences are noted in the behavioral burstiness of search and SNS in web surfing, and no significant weekday

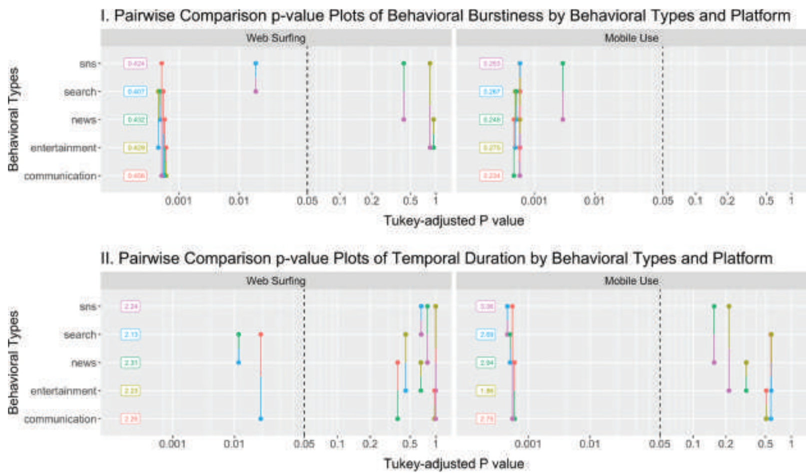

Figure 2. Pairwise comparison *p*-value plots of behavioral burstiness and temporal duration by behavioral types and platform.

differences exist in the temporal duration of entertainment and search in web surfing. Moreover, no significant weekday differences are noticed in the behavioral burstiness of news and SNS in mobile use, and no significant differences are seen in the temporal duration of communication, search, and SNS in mobile use.

Figure 4 summarizes the estimated marginal means of behavioral burstiness and temporal duration adjusted by daily intervals as well as platforms and behavioral types. The figure shows the clear circadian rhythms of behavioral burstiness, which vary across platforms and behavioral types, whereas the circadian rhythms of temporal duration are vague across platforms and behavior types.

The circadian rhythms of the behavioral burstiness of the five behaviors in web surfing demonstrate a pattern of monotonic decrease from the public time to the private time of a day. All the behaviors exhibit the greatest burstiness during public time, which decreases during hybrid time and dwindles to its daily lowest during private time. The only exception is the search behavior in web surfing, whose burstiness during public time and hybrid time differs insignificantly. However, two patterns have emerged in the circadian rhythm of behavioral burstiness in mobile use. A V-shaped circadian rhythm is observed in the behavioral burstiness of communication, search, and SNS. These three behaviors exhibit the greatest behavior burstiness during public time, which plummets to its daily lowest during hybrid time but bounces back during private time. An L-shaped circadian rhythm is noted in the behavioral burstiness of entertainment and news. The behavioral burstiness of these two behaviors is highest during public time, which drops to a lower level during hybrid time and private time. Their burstiness during hybrid time and private time differs insignificantly.

Nevertheless, insignificant circadian changes are observed in the temporal duration of communication and SNS in web surfing, and insignificant circadian changes are seen in the temporal duration of news, search, and SNS in mobile use. For entertainment and news in web surfing, their temporal duration during public time is significantly greater than that during private time. For search in web surfing, their temporal duration during public time is significantly greater than that during hybrid time and private time. For communication and entertainment in mobile use, their temporal duration during public time is significantly longer than that during private time.

Between-individual Differences in Behavioral Burstiness and Temporal Duration

Age has a significantly negative and weak effect on behavioral burstiness. Moreover, the simple main effect of age on behavioral burstiness in web surfing is consistently stronger than that in mobile use across all behaviors, except for news. The simple main effect of age on temporal duration is statistically insignificant for news and SNS in web surfing and insignificant for communication,

Figure 3. Pairwise comparison *p*-value plots of behavioral burstiness and temporal duration by week days, behavioral types, and platforms.

news, search, and SNS in mobile use at the 95% confidence level. Age has a significantly positive effect on the temporal duration of the communication and search behavior in web surfing, whereas age has a significantly negative effect on the temporal duration of entertainment in web surfing and mobile use.

Gender differences in behavioral burstiness and temporal duration adjusted by behavioral types and platforms are displayed in Figure 5. The male users' behavioral burstiness in entertainment, search, and SNS in web surfing is significantly greater than that of the female users, whereas the male users' behavioral burstiness in communication is significantly lower than that of the female users. No significant gender differences are observed in the behavioral burstiness of news in web surfing. The male users' temporal duration in communication, entertainment, search, and SNS in web surfing is significantly shorter than that of the female users, whereas no significant gender differences are seen in the temporal duration of news in web surfing.

In mobile use, the male users' behavioral burstiness in news is significantly lower than that of the female users. However, no significant gender differences are noted in the behavioral burstiness of communication, entertainment, search, and SNS in mobile use. Furthermore, in mobile use, no significant gender differences are observed in the temporal duration of all five behaviors.

In web surfing, the users' behavioral burstiness in communication significantly increases with their education level, whereas users with different education levels do not differ significantly in the

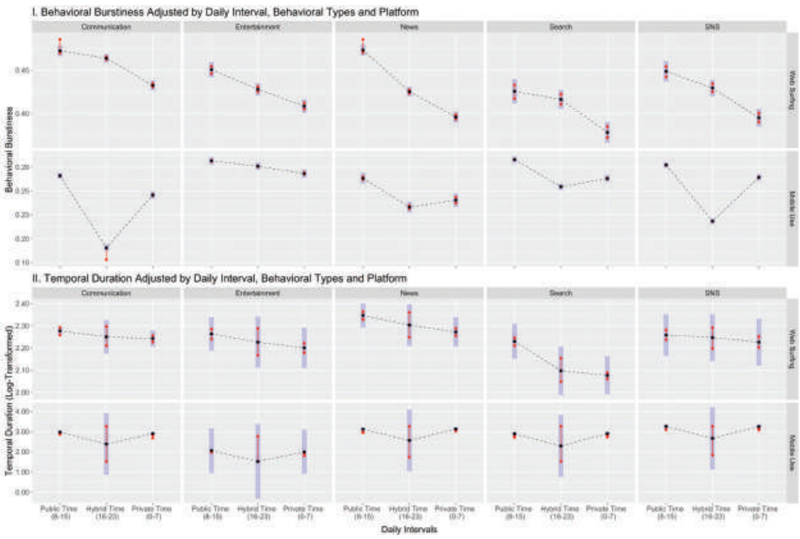

Figure 4. Estimated marginal means of behavioral burstiness and temporal duration adjusted by daily interval, behavioral types, and platforms.

The blue bars represent confidence intervals for the estimated marginal means, and the red arrows denote comparisons among them. If an arrow from one estimated mean overlaps with an arrow from another group, then the difference is not statistically significant at the 95% confidence level.

behavioral burstiness of the other four behaviors in web surfing. Users with low education levels demonstrate a significantly shorter temporal duration in communication compared with those with high/medium education levels. Users with different education levels do not differ significantly in the temporal duration of entertainment and SNS in web surfing. In mobile use, no significant differences are seen in the behavioral burstiness of communication and entertainment across different education levels. However, in mobile use, users with high education levels exhibit a significantly longer temporal duration in communication and entertainment compared with users with medium education levels.

No consistent and evident occupational differences exist in the behavioral burstiness and temporal duration of the five behaviors in web surfing and mobile use. In web surfing, no significant occupational differences appear in the behavioral burstiness and temporal duration of communication, search, and SNS. Furthermore, no significant occupational differences are seen in the temporal duration of communication, entertainment, news, and SNS in mobile use.

Conclusions and Discussion

Driven by improved computational methods and the emergence of powerful and cheap processing power (Van Atteveldt & Peng, 2018), user-generated digital traces, ranging from webpage browsing and social media messages to mobile application use, have been adopted by communication researchers to model and understand online behaviors. The current study aims to address the "*when*" question of online behaviors with digital traces, specifically, how to quantify the temporal patterns of online behaviors. Although seemingly simple, this question is an essential nontrivial issue in communication research and beyond.

This study proposes that behavioral burstiness, which is built on empty time intervals in consecutive online behaviors, can act as a complementary metric in the empirical quantification of online behaviors. This study integrates two behavioral datasets collected from the same population in Hong Kong during two periods (i.e., 2002–2004 and 2016). The study shows that the behavioral burstiness of online behaviors is important and informative. Moreover, it can unveil distinct patterns

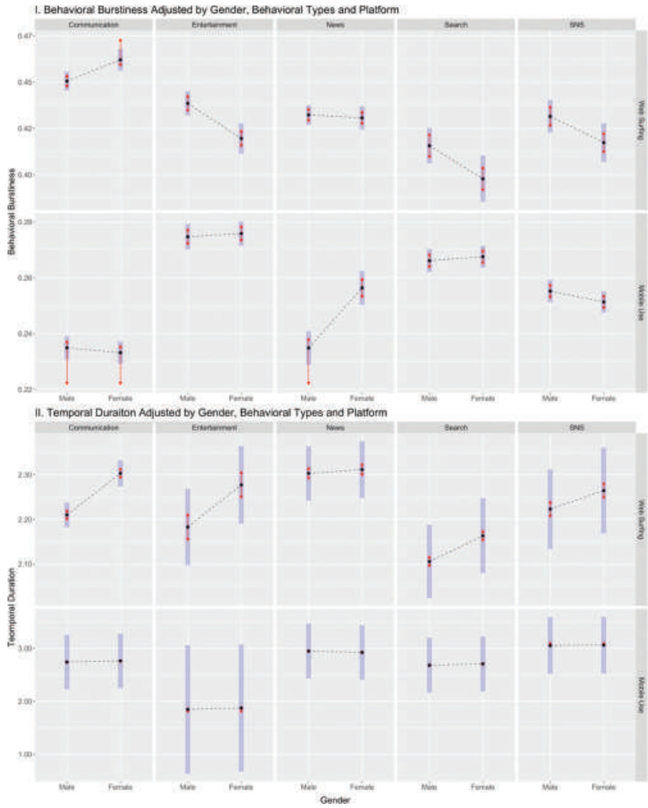

Figure 5. Estimated marginal means of behavioral burstiness and temporal duration adjusted by gender, behavioral types, and platforms.

The blue bars represent confidence intervals for the estimated marginal means, and the red arrows denote comparisons among them. If an arrow from one estimated mean overlaps with an arrow from another group, then the difference is not statistically significant at the 95% confidence level.

underlying online behaviors compared with temporal duration, which is built on the filled time intervals of online behaviors. The findings of the study can enrich our existing knowledge on online behaviors, which have methodological implications for communication research in general and media use studies in particular.

From Web Surfing to Mobile Use: Longer Duration but Lower Burstiness

When users are no longer tethered to computer cords to harness the power of the Internet (Humphreys et al., 2013), their online time is extended in mobile use compared with web surfing. Meanwhile, behavioral burstiness in mobile use is consistently lower than that in web surfing. Finding individuals' online time increasing from web surfing to mobile use is not surprising, as the Internet has become increasingly integrated into our daily lives. Nevertheless, observing online behavioral burstiness decreasing from web surfing to mobile use is unexpected. This striking difference in behavioral burstiness between web surfing and mobile use sheds light on how users organize their time to execute online behaviors in daily routines. High behavioral burstiness in web surfing implies that users' behaviors are clustered into short and separate segments of time. Meanwhile, low behavioral burstiness in mobile use implies that users' behaviors are evenly spread out over time.

This study is among the first to reveal changes in online behavioral patterns as a response to macrolevel technological development from web surfing to mobile use. Our intent is not to claim that human behaviors are technologically determined. However, individuals will undoubtedly adapt their behavioral patterns to evolving technologies. Owing to the on-the-go nature of mobile Internet, mobile devices have expanded temporal resources available to ordinary users for spending. Therefore, finding that the temporal duration of all five behaviors in mobile use is longer than that in web surfing is reasonable. Moreover, as the mobile Internet unleashes temporal and spatial constraints in Internet use, users can access the web in convenient geolocations and time periods. This advantage can substantially facilitate the schedule of online behaviors over time. Unlike in the age of web surfing when users had to condense their behaviors into intensively clustered sessions, in the age of mobile use, users can spread their behaviors more evenly over time.

From Public to Private Time: What Is (Un)changed?

This study explicitly examines whether individuals' online behavioral patterns during public time differ from or accord with online behavioral patterns during private time. How the boundary between public and private time is changed by the increasing adoption of ICTs is a long-standing concern in social research. The "anywhere, anytime" connectivity promised by mobile technologies (Green, 2002) is argued to disempower individual users' management of such a boundary (Prasopoulou et al., 2006). Online behavioral patterns characterized by empty and filled time intervals lead to different conclusions. Behavioral burstiness reveals marked differences in online behavioral patterns between private and public time, whereas temporal duration unveils indistinct contrasts between private and public time.

In web surfing and mobile use, behavioral burstiness during public time is greater than that during other daily intervals. Differences in behavioral burstiness between hybrid and private time change from web surfing to mobile use. In web surfing, behavioral burstiness during private time is significantly lower than that during hybrid time. In mobile use, behavioral burstiness during private time is either at the same level as or greater than behavioral burstiness during hybrid time. Nevertheless, drawing conclusions on differences in online behavioral patterns between public and private time with temporal duration as a metric is far from adequate. The temporal duration of certain behaviors in web surfing and mobile use does not differ between public and private time, whereas the temporal duration of certain behaviors during public time is longer than that during private time.

By discerning the clear circadian rhythms of behavioral burstiness in web surfing and mobile use, this study reveals the importance of considering intraindividual changes when assessing the behavioral patterns and social consequences of online behaviors. During the pre-electronic age, time use was directly related to the need for accurate time regulation in the economic field. Time use was standardized and constrained by external conditions, such as opening hours and work schedules (Flaherty, 2003). However, individualized and flexible uses of time have emerged with the rapid development of ICTs, which have enriched choices, improved convenience, and decreased the costs of various types of behavior, thereby leading to a reorganization of human behaviors over time. Presently, "At least principally – everybody and everything is characterized on the individual for instance, by shorter planning times, decreasing time discipline or the extension of formerly time restricted activities into new time frames" (Lenz & Nobis, 2007, p. 191). The revealed intraindividual change of online behaviors in the study implies that individual users will develop personal trajectories of online behaviors. Thus, it is reasonable to expect that such personal trajectories of online behaviors will give rise to time-varying, rather than time-invariant, consequences (Raudenbush, 2001). Uncovering the time-varying effects associated with personal trajectories of online behaviors can empower communication scholars to delineate the temporal boundary about the effects of online behaviors at an individual rather than aggregate level.

Empty Time Intervals: A New Focal Construct in Media Use Research

The current study empirically demonstrated that empty time intervals carry unique information in characterizing online behaviors, which are absent in traditional quantification of online behaviors based on filled time intervals. Empty time intervals can be considered as a focal construct in media use research in order to unravel psychological and social factors that are related to behavioral patterns of online behaviors characterized by empty time intervals.

In human dynamics research, a task-driven mechanism has been proposed and empirically tested to account for the bursty pattern of online behaviors. The task-driven mechanism argues that the bursty pattern of online behaviors is a consequence of high-priority-first (HPF) protocol in human decision-making. According to the HPF protocol, individual users will assign different priority weight to behaviors and develop a queuing process of behaviors. Those high-priority tasks in the queue will be executed first and those low-priority tasks will be held on the waiting list (Barabási, 2005).

However, systematic knowledge is missing about the psychological mechanisms underlying the bursty pattern of online behaviors. It is theoretically interesting to explore if existing media use theories, such as uses and gratifications theory and media affordance perspective, can account for the bursty pattern of online behaviors. Will gratifications obtained from earlier behavioral experience lead to the increase or decrease of empty intervals between two consecutive behaviors? How will the perceived affordance about a behavior contribute to the organization of their behaviors? It is also theoretically important to explore how individuals will assign different weights to their needs for information, entertainment, and social interaction at different time windows and how such weighted needs will lead to the circadian rhythm of behavioral burstiness revealed in the study.

Limitations and Recommendations for Future Research

Digital traces should not by default be considered an unbiased source of online behaviors (Jürgens et al., 2020). In addition to the selection bias and response bias of tracking data (Jürgens et al., 2020), we have other two potential sources of bias in the current study. The first is the respective threshold adopted in the WBD and MUD. Our observation of online behaviors is censored by the 30-min upper threshold in the WBD and the 5-s lower threshold in the MUD. Although both thresholds are implemented with empirical and practical considerations, it is necessary to acknowledge that the threshold may bias the conclusions of the study. The upper threshold in the WBD makes it impossible to document very enduring web surfing sessions, which will bring bias to the estimation of behavioral duration of webpage browsing. On the other side, the lower threshold in the MUD makes it difficult to capture very short-lived mobile app use, which will produce bias in the estimation of behavioral burstiness of mobile app use.

The second is the thematic foci of the URLs in the WBD and mobile apps in the MUD. The thematic foci of the URLs are determined by searching a list of keywords in the extracted hostnames from the URLs. Although our approach can be quite precise in classifying the URLs into different thematic foci, this approach will miss some URLs that should be assigned into a thematic category. The thematic categories of a substantial proportion of URLs in the WBD are not identifiable. The thematic foci of the mobile apps are automatically determined based on an existing category. The thematic foci of the mobile app may not well represent the users' real behavior in the app. For example, Facebook app is categorized as an SNS app while ordinary users can engage in various types of behaviors (reading news, social networking, interpersonal communication) within the app. Future studies with innovative design are needed to examine online behaviors within an app.

Moreover, tracking data can only provide observations of human behaviors with few information about psychological perceptions included. In the current study, the perceived boundary between public time, private time, and hybrid time may vary among users and change over time. However, there are no clues to directly measure or indirectly infer individuals' perception of such boundaries from the tracking data. Innovative design is needed in future research to integrate other observational data (e.g., mobile tracking of physiological traits) with tracking data which can enable a socio-psychological examination of human behavior.

This study focuses on two metrics of online behavioral patterns, that is, temporal duration characterized by filled time intervals and behavioral burstiness characterized by empty time intervals. Additional metrics are used to characterize online behavioral patterns, such as diversity of online time (Peng & Zhu, 2011) and behavioral repertoire size (Taneja et al., 2012). Future studies are needed to evaluate how behavioral burstiness differs from these metrics in understanding online behaviors. The current study examines the temporal duration and behavioral burstiness of five types of behaviors separately. Users can combine multiple types of behaviors into a session, and sequential patterns underlying the combinatorial organization of online behaviors exist (Peng & Zhu, 2020; Zhu et al., 2018). Furthermore, when the empty time intervals of one behavior on the time continuum are coupled with the filled time intervals of other behaviors, it allows researchers to empirically estimate the likelihood that multiple online behaviors can be combined into a sequential process (Peng & Zhu, 2020). Exploring how the filled and empty intervals of sessions of behaviors can reveal similar or different patterns of online behaviors as uncovered by discrete behaviors would be interesting.

Last but not least, time is an indispensable but unappreciated element in our conceptualization, operationalization, and modeling of various communicative behaviors. Digital traces offer a plethora of possibilities to explore the patterns and dynamics of underlying behaviors. The meaning of time in communication behaviors should and can be explicated in an intricate way and modeled in a sophisticated manner, with fine-grained temporal information embedded in digital traces. Our study is among the first to demonstrate empirically that a fresh perspective on time in human behavior can contribute new knowledge and unveil novel patterns in communicative behaviors. Thus, communication researchers should seriously and innovatively (re)think about time.

Disclosure Statement

No potential conflict of interest was reported by the authors.

Funding

The study is partially funded by GRF 11505119 from Hong Kong Research Grants Council and HKIDS 9360163 from City University of Hong Kong.

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References

Adam, B. (1990). *Time and social theory*. Temple University Press.

Araujo, T., Wonneberger, A., Neijens, P., & de Vreese, C. (2017). How much time do you spend online? Understanding and improving the accuracy of self-reported measures of Internet use. *Communication Methods and Measures*, *11*(3), 173–190. https://doi.org/doi:10.1080/19312458.2017.1317337

Barabási, A. L. (2005). The origin of bursts and heavy tails in human dynamics. *Nature*, *435*(7039), 207–211. https://doi.org/doi:10.1038/nature03459

Baumeister, R. F., & Vohs, K. D. (2007). Self-regulation, ego depletion, and motivation. *Social and Personality Psychology Compass*, *1*(1), 115–128. https://doi.org/doi:10.1111/j.1751-9004.2007.00001.x

Blank, G. (2017). The digital divide among Twitter users and its implications for social research. *Social Science Computer Review*, *35*(6), 679–697. https://doi.org/doi:10.1177/0894439316671698
Boase, J., & Ling, R. (2013). Measuring mobile phone use: Self-report versus log data. *Journal of Computer-Mediated Communication*, *18*(4), 508–519. https://doi.org/doi:10.1111/jcc4.12021
Candia, J., Gonzalez, M. C., Wang, P., Schoenharl, T., Madey, G., & Barabasi, A. L. (2008). Uncovering individual and collective human dynamics from mobile phone records. *Journal of Physics a-Mathematical and Theoretical*, *41*(22), 224015. https://doi.org/doi:10.1088/1751-8113/41/22/224015
Cotten, S. R., Goldner, M., Hale, T. M., & Drentea, P. (2011). The importance of type, amount, and timing of internet use for understanding psychological distress. *Social Science Quarterly*, *92*(1), 119–139. https://doi.org/doi:10.1111/j.1540-6237.2011.00760.x
Crane, R., & Sornette, D. (2008). Robust dynamic classes revealed by measuring the response function of a social system. *Proceedings of the National Academy of Sciences of the United States of America*, *105*(41), 15649–15653. https://doi.org/doi:10.1073/pnas.0803685105
De Leeuw, J., & Kreft, I. G. G. (1995). Questioning multilevel methods. *Journal of Educational and Behavioral Statistics*, *20*(2), 171–189. https://doi.org/doi:10.3102/10769986020002171
Domahidi, E. (2018). The associations between online media use and users' perceived social resources: A meta-analysis. *Journal of Computer-Mediated Communication*, *23*(4), 181–200. https://doi.org/doi:10.1093/jcmc/zmy007
Flaherty, M. G. (2003). Time work: Customizing temporal experience. *Social Psychology Quarterly*, *66*(1), 17–33. https://doi.org/doi:10.2307/3090138
Fishbein, M., & Hornik, R. (2008). Measuring media exposure: An introduction to the special issue. *Communication Methods and Measures, 2*(1-2), 1-5. doi:10.1080/19312450802095943.
Geczy, P., Izumi, N., Akaho, S., & Hasida, K. (2008). Enterprise web services and elements of human interactions. *Lecture Notes in Business Information Systems*, *7*, 263–272. https://doi.org/doi:10.1007/978-3-540-79396-0_23
Goh, K. I., & Barabási, A. L. (2008). Burstiness and memory in complex systems. *EPL (Europhysics Letters)*, *81*(4), 48002. https://doi.org/doi:10.1209/0295-5075/81/48002
Golder, S. A., & Macy, M. W. (2011). Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures. *Science*, *333*(6051), 1878–1881. https://doi.org/doi:10.1126/science.1202775
Golder, S. A., & Macy, M. W. (2014). Digital footprints: Opportunities and challenges for online social research. *Annual Review of Sociology*, *40*(1), 129–152. https://doi.org/doi:10.1146/annurev-soc-071913-043145
Golder, S. A., Wilkinson, D. M., & Huberman, B. A. (2007). Rhythms of social interaction: Messaging within a massive online network. In C. Steinfield, B. T. Pentland, M. Ackerman, and Noshir Contractor (Eds.) *Communities and technologies 2007* (pp. 41–66). London.
Goncalves, B., & Ramasco, J. J. (2008). Human dynamics revealed through web analytics. *Physical Review E*, *78*(2), 026123. https://doi.org/doi:10.1103/PhysRevE.78.026123
Gonzalez, M. C., Hidalgo, C. A., & Barabasi, A. L. (2008). Understanding individual human mobility patterns. *Nature*, *453*(7196), 779–782. https://doi.org/doi:10.1038/nature06958
Grabowski, A., & Kosinski, R. (2008). Mixing patterns in a large social network. *Acta Physica Polonica B*, *39*(5), 1291–1300. https://www.actaphys.uj.edu.pl/R/39/5/1291
Grabowski, A., & Kruszewska, N. (2007). Experimental study of the structure of a social network and human dynamics in a virtual society. *International Journal of Modern Physics C*, *18*(10), 1527–1535. https://doi.org/doi:10.1142/S0129183107011480
Green, N. (2002). On the move: Technology, mobility, and the mediation of social time and space. *The Information Society*, *18*(4), 281–292. https://doi.org/doi:10.1080/01972240290075129
Grinberg, N., Naaman, M., Shaw, B., & Lotan, G. (2013). Extracting diurnal patterns of real world activity from social media. *Seventh International AAAI Conference on Weblogs and Social Media, Boston, Massachusetts*. https://www.aaai.org/ocs/index.php/ICWSM/ICWSM13/paper/download/6087/6359
Gross, D., & Harris, C. M. (1985). *Fundamentals of queuing theory*. Wiley.
Haight, F. A. (1967). *Handbook of the poisson distribution*. Wiley.
Humphreys, L., Von Pape, T., & Karnowski, V. (2013). Evolving mobile media: Uses and conceptualizations of the mobile internet. *Journal of Computer-Mediated Communication*, *18*(4), 491–507. https://doi.org/doi:10.1111/jcc4.12019
ITU. (2006). *The regulatory environment for future mobile multimedia services: The case of Hong Kong SAR and China*. Retrieved January 31, 2020, from http://www.itu.int/osg/spu/ni/multimobile/papers/ChinaHKMobileMultimedia.pdf
ITU. (2018). *Global and regional ICT estimates*. Retrieved January 31, 2020, from https://www.itu.int/en/mediacentre/Pages/2018-PR40.aspx
Jung, E. H., & Sundar, S. S. (2018). Status update: Gratifications derived from Facebook affordances by older adults. *New Media & Society*, *20*(11), 4135–4154. https://doi.org/doi:10.1177/1461444818768090
Jürgens, P., Stark, B., & Magin, M. (2020). Two half-truths make a whole? On bias in self-reports and tracking data. *Social Science Computer Review*, 38(5), 600–615. https://doi.org/doi:10.1177/0894439319831643

Kooti, F. (2016). *Predicting and modeling human behavioral changes using digital traces* [Doctoral dissertation], University of Southern California.

Kruikemeier, S., van Noort, G., Vliegenthart, R., & de Vreese, C. H. (2014). Unraveling the effects of active and passive forms of political Internet use: Does it affect citizens' political involvement? *New Media & Society*, *16*(6), 903–920. https://doi.org/doi:10.1177/1461444813495163

Lanaj, K., Johnson, R. E., & Barnes, C. M. (2014). Beginning the workday yet already depleted? Consequences of late-night smartphone use and sleep. *Organizational Behavior and Human Decision Processes*, *124*(1), 11–23. https://doi.org/doi:10.1016/j.obhdp.2014.01.001

Lenz, B., & Nobis, C. (2007). The changing allocation of activities in space and time by the use of ICT —"Fragmentation" as a new concept and empirical results. *Transportation Research Part A: Policy and Practice*, *41*(2), 190–204. https://doi.org/doi:10.1016/j.tra.2006.03.004

Livingstone, S., & Helsper, E. (2010). Balancing opportunities and risks in teenagers' use of the Internet: The role of online skills and internet self-efficacy. *New Media & Society*, *12*(2), 309–329. https://doi.org/doi:10.1177/1461444809342697

Min, B., & Goh, K. I. (2013). Burstiness: Measures, models, and dynamic consequences. In P. Holme & J. Saramäki (Eds.), *Temporal networks* (pp. 41–64). Springer Berlin Heidelberg.

Muraven, M., & Baumeister, R. F. (2000). Self-regulation and depletion of limited resources: Does self-control resemble a muscle? *Psychological Bulletin*, *126*(2), 247–259. https://doi.org/doi:10.1037/0033-2909.126.2.247

Murthy, D., Bowman, S., Gross, A. J., & McGarry, M. (2015). Do we tweet differently from our mobile devices? A study of language differences on mobile and web-based Twitter platforms. *Journal of Communication*, *65*(5), 816–837. https://doi.org/10.1111/jcom.12176

Murthy, D., Gross, A., & Pensavalle, A. (2016). Urban social media demographics: An exploration of Twitter use in major American cities. *Journal of Computer-Mediated Communication*, *21*(1), 33–49. https://doi.org/doi:10.1111/jcc4.12144

Nelson, J. L., & Taneja, H. (2018). The small, disloyal fake news audience: The role of audience availability in fake news consumption. *New Media & Society*, *20*(10), 3720–3737. https://doi.org/doi:10.1177/1461444818758715

Neuman, W. R., Guggenheim, L., Jang, S. M., & Bae, S. Y. (2014). The dynamics of public attention: Agenda-setting theory meets big data. *Journal of Communication*, *64*(2), 193–214. https://doi.org/doi:10.1111/jcom.12088

Peng, T. Q., & Zhu, J. J. H. (2011). Sophistication of Internet usage (SIU) and its attitudinal antecedents: An empirical study in Hong Kong. *Computers in Human Behavior*, *27*(1), 421–431. https://doi.org/doi:10.1016/j.chb.2010.09.004

Peng, T. Q., & Zhu, J. J. H. (2020). Mobile phone use as sequential processes: From discrete behaviors to sessions of behaviors and trajectories of sessions. *Journal of Computer-Mediated Communication*, *25*(2), 129–146. https://doi.org/doi:10.1093/jcmc/zmz029

Perreault, M., & Ruths, D. (2011). The effect of mobile platforms on Twitter content generation. *Fifth International AAAI Conference on weblogs and social media, Barcelona, Spain*. https://www.aaai.org/ocs/index.php/ICWSM/ICWSM11/paper/view/2798

Prasopoulou, E., Pouloudi, A., & Panteli, N. (2006). Enacting new temporal boundaries: The role of mobile phones. *European Journal of Information Systems*, *15*(3), 277–284. https://doi.org/doi:10.1057/palgrave.ejis.3000617

Prior, M. (2009). The Immensely Inflated News Audience: Assessing Bias in Self-Reported News Exposure. *Public Opinion Quarterly*, *73*(1), 130–143. https://doi.org/10.1093/poq/nfp002

Raudenbush, S. W. (2001). Comparing personal trajectories and drawing causal inferences from longitudinal data. *Annual Review of Psychology*, *52*(1), 501–525. https://doi.org/10.1146/annurev.psych.52.1.501

Riedl, C., & Woolley, A. W. (2017). Teams vs. crowds: A field test of the relative contribution of incentives, member ability, and emergent collaboration to crowd-based problem solving performance. *Academy of Management Discoveries*, *3*(4), 382–403. https://doi.org/doi:10.5465/amd.2015.0097

Rodriguez, M. G., Gummadi, K., & Schoelkopf, B. (2014). Quantifying information overload in social media and its impact on social contagions. *In Eighth International AAAI Conference on weblogs and social media, Ann Arbor, Michigan*.

Ross, G. J., & Jones, T. (2015). Understanding the heavy-tailed dynamics in human behavior. *Physical Review E*, *91*(6), 062809. https://doi.org/doi:10.1103/PhysRevE.91.062809

Scharkow, M. (2016). The accuracy of self-reported internet use—a validation study using client log data. *Communication Methods and Measures*, *10*(1), 13–27. https://doi,org/10.1080/19312458.2015.1118446

Schnauber-Stockmann, A., & Mangold, F. (2020). Day-to-day routines of media platform use in the digital age: A structuration perspective. *Communication Monographs*, 1–20. https://doi.org/doi:10.1080/03637751.2020.1758336

Smith, C. D., & Scarf, D. (2017). Spacing repetitions over long timescales: A review and a reconsolidation explanation. *Frontiers in Psychology*, *8*(962). https://doi.org/doi:10.3389/fpsyg.2017.00962

Taneja, H., & Viswanathan, V. (2014). Still glued to the box? Television viewing explained in a multi-platform age integrating individual and situational predictors. *International Journal of Communication*, *8*, 2134–2159. https://ijoc.org/index.php/ijoc/article/view/2841

Taneja, H., Webster, J. G., Malthouse, E. C., & Ksiazek, T. B. (2012). Media consumption across platforms: Identifying user-defined repertoires. *New Media & Society*, *14*(6), 951–968. https://doi.org/doi:10.1177/1461444811436146

Turkle, S. (2008). Always-on/always-on-you: The tethered self. In J. Katz (Ed.), *Handbook of mobile communication studies* (pp. 121–138). MIT Press.

Ubaldi, E., Vezzani, A., Karsai, M., Perra, N., & Burioni, R. (2017). Burstiness and tie activation strategies in time-varying social networks. *Scientific Reports*, *7*(1), 46225. https://doi.org/doi:10.1038/srep46225

van Atteveldt, W., & Peng, T. Q. (2018). When communication meets computation: Opportunities, challenges, and pitfalls in computational communication science. *Communication Methods and Measures*, *12*(2–3), 81–92. https://doi.org/doi:10.1080/19312458.2018.1458084

Webster, J. G. (2009). The role of structure in media choice. In T. Hartmann (Ed.), *Media choice. A theoretical and empirical overview* (pp. 221–233). Routledge.

Webster, J. G., & Wakshlag, J. J. (1982). The impact of group viewing on patterns of television program choice. *Journal of Broadcasting*, *26*(1), 445–455. https://doi.org/doi:10.1080/08838158209364012

Wirth, W., Von Pape, T., & Karnowski, V. (2008). An integrative model of mobile phone appropriation. *Journal of Computer-Mediated Communication*, *13*(3), 593–617. https://doi.org/doi:10.1111/j.1083-6101.2008.00412.x

Xu, P., Wu, Y., Wei, E., Peng, T. Q., Liu, S., Zhu, J. J. H., & Qu, H. (2013). Visual analysis of topic competition on social media. *IEEE Transactions on Visualization and Computer Graphics*, *19*(12), 2012–2021. https://doi.org/doi:10.1109/TVCG.2013.221

Yan, D. C., Wei, Z. W., Han, X. P., & Wang, B. H. (2017). Empirical analysis on the human dynamics of blogging behavior on github. *Physica A: Statistical Mechanics and Its Applications*, *465*(1), 775–781. https://doi.org/doi:10.1016/j.physa.2016.08.054

Zaheer, S., Albert, S., & Zaheer, A. (1999). Time scales and organizational theory. *The Academy of Management Review*, *24*(4), 725–741. https://doi.org/doi:10.5465/amr.1999.2553250

Zerubavel, E. (1979). Private time and public time: The temporal structure of social accessibility and professional commitments. *Social Forces*, *58*(1), 38–58. https://doi.org/doi:10.2307/2577783

Zhang, L., Zheng, L., & Peng, T. Q. (2017). Structurally embedded news consumption on mobile news applications. *Information Processing & Management*, *53*(5), 1242–1253. https://doi.org/doi:10.1016/j.ipm.2017.04.009

Zheng, L. N., Mai, F., Gordon, D. M., & Nickerson, J. (2019, December 15–18). Bursty coordination in online communities. In *Proceedings of International Conference and Information Systems (ICIS) 2019*, Munich, Germany.

Zhu, J. J. H., Chen, H. X., Peng, T. Q., Liu, X. F., & Dai, H. X. (2018). How to measure sessions of mobile device use? Quantification, evaluation, and applications. *Mobile Media & Communication*, *6*(2), 215–232. https://doi.org/doi:10.1177/2050157917748351

Zhu, J. J. H., & He, Z. (2002). Perceived characteristics, perceived needs, and perceived popularity – Adoption and use of the internet in China. *Communication Research*, *29*(4), 466–495. https://doi.org/doi:10.1177/0093650202029004005