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The Impact of Digital Media on Daily Rhythms: Intrapersonal Diversification and Interpersonal Differentiation

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Digital media are popularly regarded as one of the central identifiers of postmodern life. However, systematic examinations that address how digital media and their development affect lives and contribute to social change are lacking. To address this issue, we used two national representative samples from 2000 and 2015 (comprising 5,375 and 4,134 people, respectively). We constructed a sequence of daily activity rhythms based on diary surveys and assessed the influence of computer and mobile phone accessibility and use. The results showed that (1) digital media increased intrapersonal diversification and interpersonal differentiation across the years although variations existed regarding media modalities, media accessibility and usage, and time frame; (2) computers had a stronger effect than mobile phones; and (3) actual media use time had a direct influence on the allocation of daily activities. These findings reveal a media effect on daily activity rhythms, a form of what this study calls "postmodern transformation."

Keywords: media effect, temporal rhythm, daily activities, sequence analysis, digital media, temporality

Among various technologies, digital media have been regarded by some as the central identifier of contemporary life (Sullivan & Gershuny, 2018). More than half of the world population considered themselves Internet users in 2019; as compared with about 12% to 13% of the population in 2005 (Statista, 2020). As a result of the changes from Web 1.0 to Web 3.0, digital media have become an integral part of the daily activities of the average consumer and worker. Moreover, with drastic changes in their modality and functions, such digital media largely shape and reshape a person's allocation of time and space (Schulz,

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2004), thus reshaping the entire structure of day-to-day life. Through allocation of daily activities, digital media further exert a substantial influence on individuals' physical and mental health (Barber & Jenkins, 2014), interpersonal relationships (Hampton, 2019; Katz & Rice, 2002), and working efficiency (Ninaus, Diehl, Terlutter, Chan, & Huang, 2015). However, there has been no systematic comparison of daily activities with versus without the assistance of digital media. Moreover, limited studies considered how the digital media modality changes affect intrapersonal diversification (i.e., increased life options people choose) and interpersonal differentiation (i.e., increased heterogeneity among people) in daily activities. These phenomena reflect the postmodernization trend in our daily lives. And such effect is the central concern of the social acceleration theory (Rosa, 2013), which refers to how technological development increases overall social changes and pace of life.

The current study examines the role that digital media play in the organization of daily activities. Such organization is affected by both social structure and individual variabilities. To explore the effect of digital media on changing daily activities, we used two diary surveys from national representative samples in 2000 and 2015. Furthermore, we distinguished between accessibility and the extent of actual use.

This study contributes to the literature on social acceleration theory and media effect. It highlights the social meanings of temporal allocation and provides insights into the postmodernization trend in our daily lives. Moreover, the research sheds light on a new methodology for exploring this form of media effect by quantifying daily activities into sequences. Practically the study aims to aid platform designers in examining and comprehending peoples' temporal characteristics. It also highlights the role of digital device penetration in improving aspects of life.

Literature Review

Postmodernization in Contemporary Life

De-standardization is a typical phenomenon under the postmodern transformation of contemporary life (Brückner & Mayer, 2005; Elzinga & Liefbroer, 2007; Lund & Gronow, 2014). It describes a trend in which people are less constrained by dominant norms, and individual agency is the determining factor in decisions of how to lead one's life. Consequently, both interpersonal differentiation and intrapersonal diversification increase (Brückner & Mayer, 2005; Elzinga & Liefbroer, 2007; Lund & Gronow, 2014; Petev, 2013).

Previous literature has examined such social transformation by investigating the life courses of individuals. In recent years, researchers have examined daily activities as a means of assessing social change over time (Elzinga & Liefbroer, 2007; Robinson, 2002). The organization of daily activities (i.e., social practices) is a vital window through which one can view social transformations because it reflects both structural influence and individual agency (de Certeau, 1984; Lefebvre, 1991). Furthermore, because daily activities are often conducted subconsciously, they can passively reflect the characteristics of our time and habitual norms.

Temporal rhythm, which describes the repeated time structure of practices (Lefebvre, 2004), has been a central perspective for quantifying the current structure of social practice and society as well as historical changes in said structure. The temporal structure of society is highlighted by Rosa's (2013) theory of social acceleration, where it interlaces with both social change and technological development. Empirically, several studies (Holm et al., 2016; Lund & Gronow, 2014) observed a slight change by comparing daily eating rhythms over the last 20 years. They interpreted the process of de-standardization in irregular times of eating, shortened eating durations, an increased probability of multitasking while eating, and a decreased likelihood of eating with social ties and in a kitchen. They found that although typical eating rhythms remained stable, people had more diversified rhythms in 2012 compared with those in 1997.

Digital Media and Postmodern Life

According to the social acceleration theory (Rosa, 2013), technological development accelerates social change and life pace. Media technologies are important when focusing on the modern and postmodern transformations of people's lives because they produce distanciation of time and space, disembedding of social life, and reflexive appropriation of knowledge about social life (Giddens, 1990). Furthermore, as opposed to mass media, where institutions and specialists dominate, digital media decompose such institutionalized manufacturing by encouraging lay people to participate and create (Gerhards & Schäfer, 2010). Consequently, digital media use is regarded as an important influencer of social acceleration (Sullivan & Gershuny, 2018).

The Effect of Media Use on Daily Rhythms

To consider the role of media use in daily activities, it is necessary to investigate both intrapersonal and interpersonal aspects. Both reflect postmodern social changes. Interpersonal differentiation takes a relational view and examines the cross-sectional differences among people. It considers the phenomenon in which life states and sequences have become dispersed and can only describe a decreasing part of the population, that is to say, de-standardization (Brückner & Mayer, 2005). Intrapersonal diversification takes an individualistic view and examines changes within individual daily activities. It considers the phenomenon that the number of distinct stages across daily activities has increased. The two phenomena are not necessarily correlated (Brückner & Mayer, 2005). However, media use has a distinct influence on both these aspects.

Convergence or Differentiation

Related literature exhibits the connection between digital media use and heterogeneity among people. First, due to convergence between media and non-media activities, classical norms are forced to transform to new norms. For example, the concept of offline popularity is closely related to self-esteem, but the concept of online popularity is alternately related to sociability (Zywica & Danowski, 2008). Through the use of a digital media platform, new norms of good citizenship have emerged (Baldwin-Philippi, 2012).

Second, digital media provide opportunities for like-minded individuals to gather, create subcultures, and establish group norms across time and space (Wagner, Hassanein, & Head, 2010). Then, traditional norms cannot uniformly direct all lifestyles. Furthermore, such norms that overlap among different online groups are decreasing due to psychological preferences, recommendation systems, and limited time and attention resources (Haim, Graefe, & Brosius, 2018). This leads to the heterogeneity of attitudes and opinions, and possibly differentiated lifestyles. However, contrary findings exist where communities are duplicated rather than isolated (Webster & Ksiazek, 2012).

Displacement or Diversification

In terms of changes happening within individual daily lives, a major concern is that computers and mobile phones have displaced other activities, especially those that involve socializing with friends. This is because digital media contain features that attract people to use them excessively. This is known as the displacement hypothesis (Mutz, Roberts, & van Vuuren, 1993). For example, Twenge, Joiner, Rogers, and Martin (2018) found that social media use by adolescents significantly decreased their non-screen activities, thereby increasing the possibility of depression. Digital media can further decrease the quality of socialization because people are always connected and ask for instantaneous responses (Turkle, 2011). However, contrary arguments have also been proposed. Studies tracing the media's effects on people's use of time since the mid-1990s found no lower participation in daily activities for digital media users compared with nonusers (Robinson, 2011; Robinson, Kestnbaum, Neustadtl, & Alvarez, 2000). Even if digital media have displaced activities, these can only be described as home-based media activities, such as watching TV (Thulin & Vilhelmson, 2006). Moreover, the simulation hypothesis states that digital media use is just an imitation of real-life experience, especially with the emergence of social networking sites. Thus, this use does not necessarily have negative effects and can even enhance people's lives. Active online users are more prosocial, contact others more, and have more close friends (Robinson et al., 2000). In this way, digital life corresponds to real life.

Moreover, digital media and online services use can increase the size and diversity of a person's social relations (Hampton, Sessions, & Her, 2011). Online photo sharing further increases the likelihood of having a close friend who has a different political ideology. One's social network constitution is widely used as a proxy measure of an individual's lifestyle because social ties reflect individual sociability in specific domains (e.g., membership in volunteer groups reflects a habit of altruistic work), and specific social groups form and enhance distinct norms and values (Petev, 2013). Thus, diversified personal networks brought by digital media likely contribute to varied daily activities.

Through online participation and networking, digital media further push people to engage in offline activities. Empirical studies have found that the use of digital media raises the possibility of political participation (Boulianne & Theocharis, 2020) and health-benefit behaviors (Althoff, Jindal, & Leskovec, 2017). People then visit public spaces and religious places more, and are more likely to engage in leisure and organizational communities (Katz & Rice, 2002). This, in turn, can increase one's network diversity (Hampton, Lee, & Her, 2011).

Theoretical Analyses and Research Hypotheses

Summary of Theoretical Foundations

A review of the literature yielded some specific problems in this area. First, the sociology of technology and modernity has paved the way for theory construction. However, to the best of the authors' knowledge, there is a lack of qualitative evidence on how technological development contributes to life-pace acceleration. Although social practice provides a promising approach to answering theoretical questions, the changes in and determinants of daily rhythm have not been adequately examined.

Second, the prevalence of the Internet and digital media have created a new situation in terms of social acceleration in current society. Compared with previous media technologies, mobile phones have largely reshaped the time–space relationship (Murnane, Abdullah, Matthews, Choudhury, & Gay, 2015; Turkle, 2011). This poses questions as to the current pace of life. It is also essential to view the pace of life from a longitudinal perspective to understand technological acceleration (the differences among different types of digital media) and its relationship with changes in contemporary life.

Third, media effect studies usually take a monophonic perspective. They often investigate one technology (e.g., comparing people who use or do not use the technology), adopt cross-sectional comparisons (e.g., comparing different media generations in the same year), or focus on one context of use (e.g., comparing the effect of the same media over the years). Although these studies provide a particular perspective, they cannot represent the full scope of a media effect. For example, it is unknown whether people without computers and mobile phones can maintain the same pace of those with computers and mobile phones over the years. Hence, to illustrate the influence of digital media on the organization of daily activities and to reveal social change, a systematic comparison articulating the influences of year, media modality development, and media accessibility/use patterns is needed.

Interpersonal Differentiation and Intrapersonal Diversification Hypotheses

Both theories of modernity and of social acceleration regard technologies as a priority. Among various technologies, digital media are vital because they impact and influence methods of communication, production, and consumption. The accessibility and use of media represent passive and active aspects of the human–technology relationship. Logically, accessibility provides the basis for media use. Having or not having access to digital media, and use of said media, are connected to social saturation (Tsetsi & Rains, 2017; van Deursen & van Dijk, 2011). Just the presence of a mobile phone can become a stressor for some (Ninaus et al., 2015) while physical use further enhances these feelings. Hence, it is necessary to examine both accessibility and use. In comparing individuals, it is possible to see increasing differences in daily rhythms (i.e., differentiation) because a dominant lifestyle no longer guides what one's life looks like. When reviewing the characteristics of individual rhythms, it is possible to see increasing life options regarding daily activities (i.e., diversification). The following hypotheses were proposed in this research:

H1: Access to and the use of digital media are more likely to differentiate people from each other in daily activities (the interpersonal differentiation hypothesis).

H1a: *There will be a higher degree of differentiation in daily activities among those with Internet and digital media access compared with those who lack access to either or both (the access effect on differentiation).*

H1b: *There will be a higher degree of differentiation in daily activities among those who use digital media more (the use effect on differentiation).*

H2: *Access to and the use of digital media are more likely to diversify people's daily activities (the intrapersonal diversification hypothesis).*

H2a: *People with closer access to digital media will engage in more distinct types of daily activities (the access effect on diversification).*

H2b: *People who use digital media to a heavier extent will engage in more distinct types of daily activities (the use effect on diversification).*

Digital Media Modality Hypotheses

When thinking about the role of digital media, it is necessary to consider modality change over the years (i.e., technological development). Digital media devices (i.e., computers and smartphones) have been regarded as the most important innovations affecting people's lives in recent years. Compared with computers, smartphones are more embedded in daily activities due to their portability and availability (Schrock, 2015). The roles smartphones and computers play in the organization of daily activities then become different. Within the same platform and the same period, self-expressions delivered through mobile phones are more individualistic and agentic than those delivered through computers (Murthy, Bowman, Gross, & McGarry, 2015). Via a mobile device, people can carefully reflect on their daily activities and foster a concept of self (Ling, 2004). These perceptional distinctions reflect lifestyle changes. That means a smartphone may have a closer connection to a differentiated and diversified lifestyle than would a computer. Furthermore, researchers have considered breadth of access. Although smartphones are regarded as a new technology, mobile-only Internet users have been found to have a disadvantaged social status when compared with multimodal Internet users in recent years (Tsetsi & Rains, 2017). Having multiple access routes to the Internet increases the variety of online activity and local social capital because the mode of access is related to engagement in different activities, skills to access information, and the volume of information people can reach (Reisdorf, Fernandez, Hampton, Shin, & Dutton, 2020). This indicates that the situation might be different depending on how many digital media devices an individual has access to and which digital media devices an individual uses for access. The following hypothesis was proposed in this research:

H3: *There will be differences in accessing multimodal digital media devices, accessing mobile phones only, accessing computers only, and no digital media access on (a) differentiation and (b) diversification. Additionally, the effect size will be in descending order among these four conditions.*

Time-Frame Hypothesis

Moreover, it is necessary to distinguish digital media technologies in various time contexts because the social meanings of "computer" and "smartphone" have varied over the years. At the turn of the century, mobile phone adopters were related to early advantages and structural disparities. However, throughout and subsequent to 2010, the role of the social environment (e.g., urbanness) on mobile phone adoption has dissolved (Rice & Pearce, 2015). Smartphone-only Internet users have since been profiled as lower-income and less-educated digital users (Tsetsi & Rains, 2017).

Social media and other online services, which have emerged with smartphones, provide a rich environment for self-representation and socialization (Hampton, Lee, & Her, 2011; Robinson et al., 2000). They have enhanced widespread attachment to technologies and have largely strengthened the role of digital media in the daily activities of the average individual (Hampton, 2019; Murnane et al., 2015). They have made it more likely for people to gain exposure to diverse information, enhance their interests, and establish new and more complete identities. Therefore, a time shift possibly intensified the media effect on differentiation and diversification. Furthermore, in recent years, the smartphone may have had a higher impact on everyday activity transformation than both its usage in earlier years (i.e., around the turn of the century) and computers in the same era. H3 posits a positive influence of accessing multimodal digital media devices, accessing mobile phones on differentiation and diversification compared with accessing computers and no digital media access. Based on H3, we hypothesized that such media modality effect is stronger in recent years compared with distant years:

H4: There will be an interaction effect between year and media modality effect (H3) on (a) differentiation and (b) diversification such that the media modality effect is larger in recent years compared with distant years.

This hypothesized relationship is shown in Figure 1.

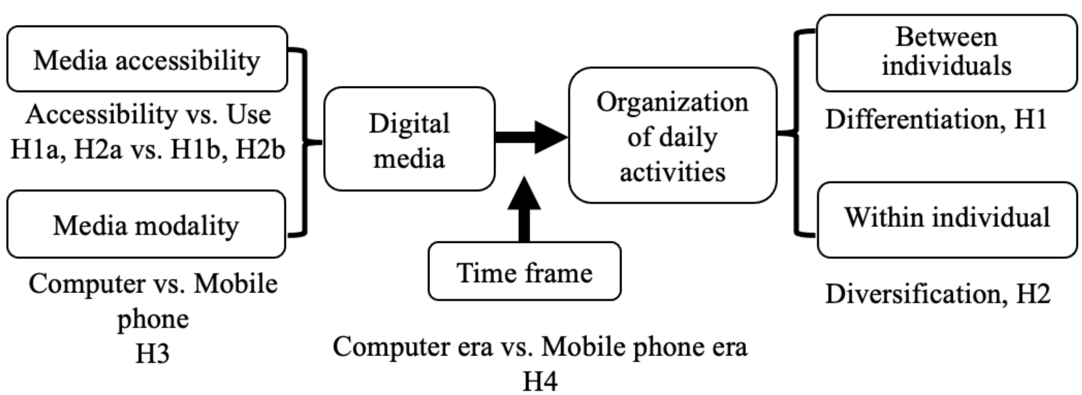

Figure 1. Theoretical model of media and the organization of activity rhythm.

Methods

Data Selection

The data came from two United Kingdom Time Use Surveys that circulated from 2000 to 2001 and from 2014 to 2015, respectively (Gershuny & Sullivan, 2017; Office for National Statistics, 2000). These surveys were conducted independently by separate organizations; however, the use of the same sampling methods and metrics ensures adequate comparability of the two. Respondents in the representative samples from the United Kingdom were invited to complete a diary questionnaire of their daily activities on weekdays and weekends. The date was randomly selected across one year. The respondents were asked to report their activities in consecutive order in terms of who they were with and where they were, from 4 a.m. of the selected day to 4 a.m. of the next day. Additional questions were used to collect their demographic information.

We restricted the samples used to the working population (aged 18–65 years old) and their weekday activities. Findings indicate significant differences between weekday and weekend rhythms (Murnane et al., 2015). Compared with weekends, a weekday rhythm is more affected by social statuses, such as occupation and educational level (Jiang, Ferreira, & González, 2012). Therefore, we selected weekday rhythms to represent daily activities as the first step of exploration. Moreover, we selected people who had complete demographic information regarding items in Table 1. In total, 5,375 and 4,134 diary days were obtained for 2000 and 2015, respectively, meaning that data from 9,509 individuals were eligible for the subsequent analysis. The detailed demographic information can be seen in Table 1.

Table 1. Sociodemographics of the Participants.

Focal factors	Item	Percentage in 2000 (%)	Percentage in 2015 (%)
Gender	Male	45.43	46.06
	Female	54.57	53.94
Age group (years)	18–24	12.15	11.56
	25–44	48.13	42.89
	54–65	39.72	45.55
Family income group (pounds per year)	< 2610	2.46	0.99
	2610–5210	7.70	1.31
	5211–10430	11.81	5.15
	10431–15640	14.12	9.39
	15641–20860	14.23	9.12
	20861–33800	24.50	29.95
	33801–41000	7.93	13.79
	41001–46000	4.20	5.95
	46001–55000	3.44	8.32
	55001–80000	5.00	8.78
	> 80001	4.60	7.26
Economy activity	In employment	73.54	74.67
	Unemployed	2.27	3.41
	Inactive	24.00	21.67
	Unclassified	0.19	0.24
Marital status	Single	18.75	22.69
	Married	73.58	66.69
	Divorced/widowed	7.67	10.62
Computer accessibility	No computer	39.37	3.46
	Home computer, no Internet access	17.99	6.10
	Home computer and Internet access	42.64	90.45
Mobile phone accessibility	No mobile phone	17.67	2.25
	Mobile phone. No Internet access	80.91	22.42
	Mobile phone and Internet access	1.41	75.33
n		5375	4134

Sequence Construction

The activities of a diary day were collected in 10-minute units in sequential order (i.e., a total of 144 steps per day). We constructed a daily activity rhythm for each participant. Following the United Kingdom Time Use Surveys' major activity classification (Gershuny & Sullivan, 2017; Office for National

Statistics, 2000), all activities were categorized into 10 major types (supplementary material,[2] Table A1). Thus, a person's daily activity rhythm involved 144 steps, each being one of the 10 types of activities. An example of a user's daily activity rhythm is "Personal care—Travel—Employment—Travel—Social life—Personal care." Figure 2 shows representative sequences across years and levels of use time. Figure 3 shows the transition percentages among the distinct daily activity types in sequential order.

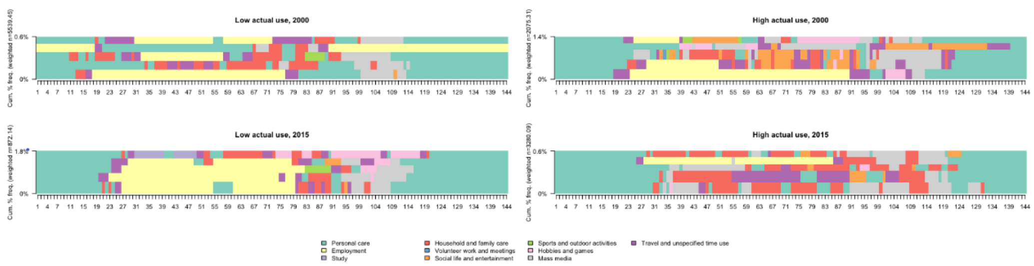

Figure 2. The top five representative sequences across the year and use time. The level of representation is measured by the frequency.

[2] Supplementary materials are accessible via Open Science Framework at https://osf.io/ue462/?view_only=d292ad20841d43bb83bf4454fa72fe4d.

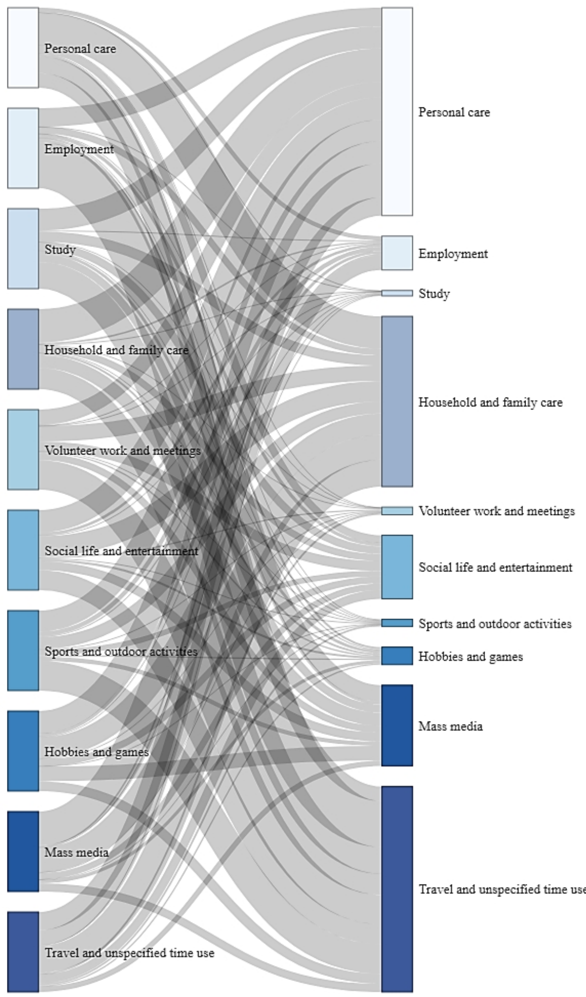

Figure 3. Transition percentages among the daily activity types.

Measurements

Interpersonal Differentiation

Differentiation refers to variations between individual rhythms. The more differences that exist among people, the more differentiated the people's daily rhythms are.

To quantify interpersonal differentiation, a sequence-based difference matrix was calculated for all pairs of individuals. A review by Studer and Ritschard (2016) summarized three distinct aspects of sequences: Timing (the temporal position when each activity starts and ends), sequencing (the temporal order of the activities), and duration (the total time length of each activity within a sequence). They suggested the use of Hamming distance (HAM), chi-square distance (CHI2), and subsequence vectorial representation metric (SVR), where the exponential weight of spell length was set to zero) to respectively measure these three aspects, as each metric is sensitive to one time dimension and insensitive to the other two (Studer & Ritschard, 2016). The Spearman correlations among the metrics in this study were $r_{HAM,\ CHI2}$ = .548, $r_{HAM,\ SVR}$ = .100, and $r_{CHI2,\ SVR}$ = .182. Because the correlation between HAM and CHI2 was relatively high, we chose to drop the differentiation of duration in the analysis. It should be noted that, although the duration and timing were overlapped empirically, they are conceptually distinct. The two concepts may not always be that strong in other contexts.

We then used discrepancy analysis to test the explanatory power of different variables on the differentiation among individuals. Discrepancy analysis follows the logic of analysis of variance. Based on the discrepancy matrix, it analyzes which individual-level factors can explain the differences among all the sequences (Studer, Ritschard, Gabadinho, & Müller, 2011). The analysis was adjusted by individual weights. This was done to control sampling bias and ensure that results could be generalized to the whole population. Weight was calculated by the original project designers by comparing the sample distribution with the population distribution in terms of gender, age, and region (Gershuny & Sullivan, 2017; Office for National Statistics, 2000).

Intrapersonal Diversification

Diversification in this study referred to an increase in the life options people chose. The diversity of life options was represented by the number of distinct major activities that occurred within a diary day. That is, the more types of activities a person performed in a day, the more diversified their daily rhythm was.

In the literature, the entropy index is linked to variation (Fussell, 2005) and diversity (Widmer & Ritschard, 2009). However, within-sequence entropy considers both the total duration and frequency of distinct activities within a rhythm. Intrapersonal diversification in this study was not related to activity duration. Therefore, the number of distinct activities was more suitable than entropy measures.

Digital Media Accessibility and Use

First, we focused on accessibility and tangible use of computers and mobile phones. Apart from theoretical considerations, we adopted these two indices to complement each other. Accessibility was identified by the self-reporting of home facilities. However, this metric tracked and measured accessibility at the family, not individual, level. Actual digital media use time could represent whether or not people were media users. However, it was measured throughout the diary day. It may be confounded with the conduct of daily activities, especially when regarded as an exclusive activity block.

In terms of media accessibility, computer households were scored as 1 = "No home computer," 2 = "Home computer without Internet access," or 3 = "Home computer with Internet access." Similarly, mobile phone households were scored as 1 = "No mobile phone," 2 = "Mobile phone without Internet access," or 3

= “Mobile phone with Internet access.” An interaction term between mobile and computer accessibility was then created.

Second, we identified the actual digital media use time, which was measured as the percentage of time during the diary day spent using computers, mobile phones, or tablets. In 2000, computer and Internet use was measured as an independent activity among the activity codings. In 2015, researchers implemented a more precise measurement of media use. They asked participants to report whether they used media devices in every reported activity. This regarded digital media as an embedded device. We generated two actual use-time indices based on the measurements. First, to compare the years, we adopted computer and Internet use as independent activities and calculated the percentage of time during the diary day spent under the related categories. It should be noted that among the activities related to digital media (e.g., gaming, communicating, information searching, and unspecified use by computing/on the Internet), programming was excluded from the calculation due to the notion that this activity is typically related to work rather than leisure. Second, to show the real effect of actual digital media use time, we calculated the percentage of time during which activities were done with computers, mobile phones, or tablets throughout diary days in 2015. The results are shown in the supplementary material. Another concern was that the newly added question about digital media as an embedded device might have changed the way people reported digital media use as a primary activity. As examined by Gershuny and colleagues (2020), nonsignificant differences existed between reported digital media use as a primary activity and real behavior in a similar situation.

Sociodemographics

We also included individual sociodemographic data, such as gender, age group, marital status, family income, and socioeconomic status, as control variables.

Analysis Strategies

All data processing and analysis were conducted using software R (R Core Team, 2017).

Results

Interpersonal Differentiation of Daily Activities

To test changes in interpersonal differentiation, a discrepancy analysis was conducted on the differences in daily activities. We discretized the percentage of actual use time into two upper and lower levels by 50% ranking order. The results are shown in Table 2 and Figure 4.

First, we examined the factors that influenced sequence differentiation in the sequencing differences (Table 2, right column). It was found that the variation was not associated with all types of media use or year differences (2000 and 2015). Second, we examined factors influencing sequence differentiation in the timing differences (Table 2, left column). Media accessibility and the interaction between modalities (i.e., computer and mobile phone) showed no substantial differences across the groups in the model (Table 2, left column, which rejects H1a and H3a). There were also no differences considering the three-way interaction among year, computer accessibility, and mobile accessibility; thus, we rejected H4a.

However, actual media use exerted a significant effect on sequence differentiation in the timing differences. First, actual media use time differentiated people's daily activity sequences in terms of timing (F = 2.641, p < .01; H1b supported). The more people used digital media, the higher the probability that they had different rhythms. Second, its effects varied by year ($F_{year \times actual\ use}$ = 2.982, p < .01; H4a partially supported). When we looked at the influence separately by year (Figure 4), it differentiated the daily rhythms in the mobile phone era. Furthermore, we looked into the model of digital media as embedded devices (see supplementary material, Table A2). The actual use time showed a similarly significant effect in 2015 whereas computer accessibility had an influence on the heterogeneity among people in 2015 (F = 1.927, p < .05; Table A2). The mean discrepancy level of the "no home computer access" condition was higher than that of the "computer and Internet access" condition (M_1= 42.30; M_2= 41.36).

Table 2. Multivariate Discrepancy Analysis of the Differentiation Among Daily Rhythms.

DV	Differentiation in timing (HAM)	Differentiation in sequencing (SVR)
Year	13.360***	0.905
Family income group	3.139**	0.736
Economy activity: unemployed[a]	4.216***	1.028
Economy activity: inactive[a]	34.498***	1.462
Economy activity: not classifiable[a]	2.121	0.007
Gender (2 = female)	7.863***	0.681
Marital status: married[b]	3.226**	0.520
Marriage status: divorced[b]	2.046	0.283
Age group	4.183***	0.801
Percentage of media use time[c]	2.641**	0.335
Computer accessibility	1.789	0.243
Mobile accessibility	1.596	0.311
Computer accessibility × mobile accessibility	1.823	0.707
Year × family income group	5.064***	1.458
Year × economy activity: unemployed	8.425***	2.160
Year × economy activity: inactive	70.519***	2.292
Year × economy activity: not classifiable	2.326	0.008
Year × gender	14.988***	0.860
Year × marital status: married	5.134***	0.751
Year × marital status: divorced	2.002	0.426
Year × age group	6.418***	1.257
Year × percentage of media use time	2.982**	0.288
Year × computer accessibility	1.939	0.238
Year × mobile accessibility	1.253	0.251
Year × mobile accessibility × computer accessibility	1.237	0.336
Total	38.343***	1.091

Note. Model using media use as an independent activity in 2000 and 2015.
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.
[a]Ref: In employment.
[b]Ref: Single.
[c]Seperated into two groups.

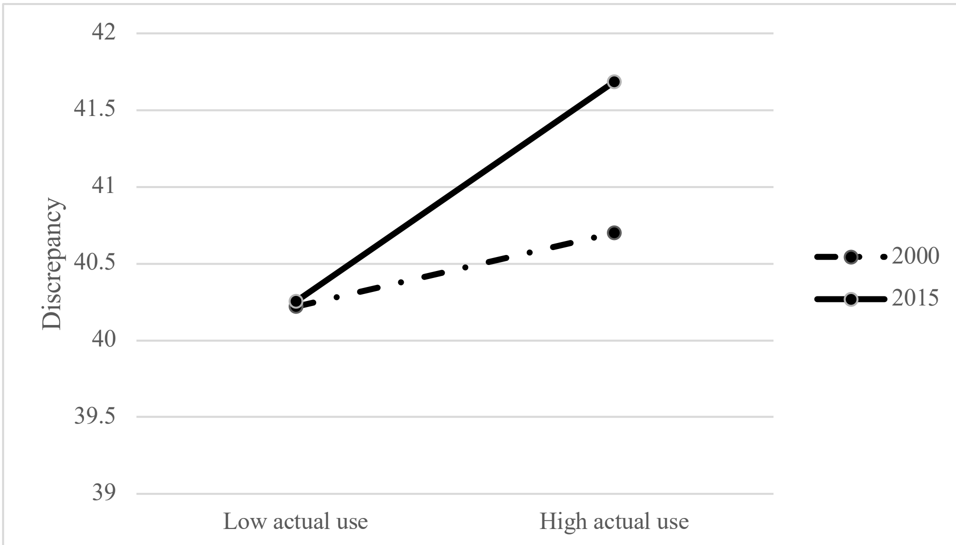

Figure 4. The in-group discrepancy based on timing across the year and use time.

Third, to further explore the within-group discrepancy across a diary day, we performed additional discrepancy analyses on each of the 144 steps and came up with Figure 5. Compared with the earlier year, the actual use time demonstrated greater differentiation among people in recent years. The differences were mainly in the morning (6 a.m.–12 p.m.) and evening (8 p.m.–4 a.m., the next day) schedules. In 2000, the daily activities were more different in the morning and less different in the late evening compared with those in 2015. When we looked at the role of actual media use time, the major difference was between 3 p.m. and 12 a.m. in 2015. High media use made people’s activities more heterogeneous from each other whereas low media use made people’s activities more homogenous with each other.

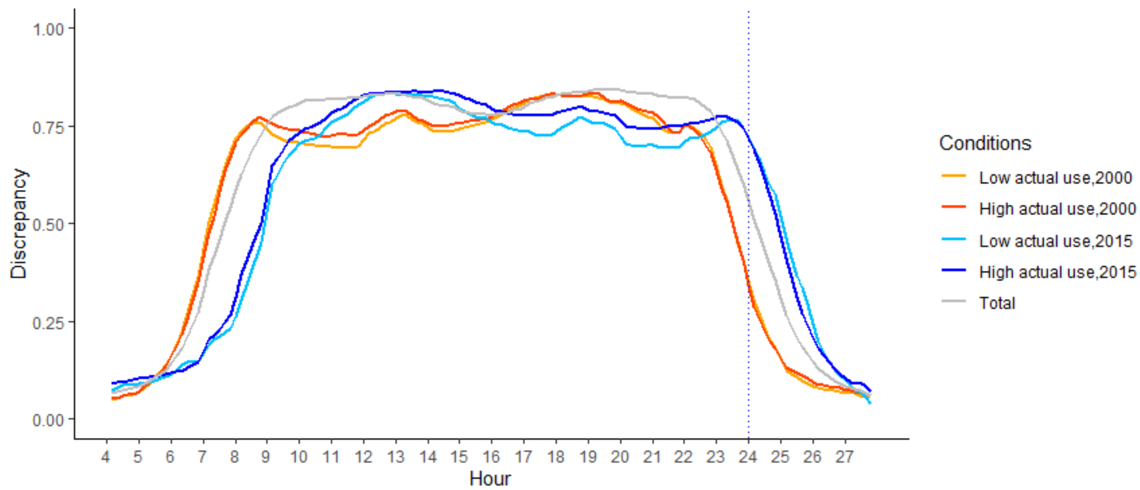

Figure 5. The time evolution of the in-group discrepancy based on timing across the year and use time. A diary day starts at 4 a.m. (4 in the x-axis) and ends at 4 a.m. the next day. A higher discrepancy score means in-group members' rhythms are more different from each other at time point t. Medium actual use is the second third of actual use time by rank. High actual use is the third third of actual use time by rank. Total is the total discrepancy among all the individuals at a given time point.

Intrapersonal Diversification of Daily Activities

Next, we investigated the media effect on within-person rhythm characteristics (i.e., diversification). A regression analysis was conducted. The results are shown in Table 3. After controlling for demographics and adjusting for individual weights among the population, a positive effect of computer accessibility was found on individual diversity (β = 0.131, p < .05). Computer accessibility increased the number of life activities in which people engaged during a day. There was no main effect of mobile accessibility or interactions among the year and computer and mobile phone accessibility. These results partially support H2a. In addition, the interaction effect between computer and mobile accessibility, and the interaction effect of year and computer and mobile accessibility were not significant. H3b and H4b were rejected.

Meanwhile, actual media use time significantly increased activity diversity (β = 8.355, p < .001; H2b supported). The effect varied further over the years (β = −2.383, p < .001; H4b partially supported). When looking at the relationship (Figure 6), a simple slope analysis showed only a stronger media use time effect in 2000 (β_{2000} = 5.97, p < .001; β_{2015} = 3.59, p < .001). In that year, using digital media increased the diversity in people's daily activities whereas in 2015, the effect still existed, but became smaller. Furthermore, we looked into the model of digital media as embedded devices (supplementary material, Table A3), and the digital media use increased diversity in 2015 (β = 3.589, p < .001). This partially supports H2b.

Table 3. Regression Analysis of Factors That Affect Intrapersonal Diversity.

DV:	Diversity
Year	−0.019 (0.154)
Family income group	−0.032* (0.015)
Economy activity: unemployed[a]	0.359 (0.201)
Economy activity: inactive[a]	−0.317*** (0.082)
Economy activity: not classifiable[a]	0.651 (0.690)
Gender (2 = female)	0.186** (0.065)
Marital status: married[b]	0.096 (0.056)
Marital status: divorced[b]	−0.076 (0.089)
Age group	0.254 (0.142)
Percentage of media use time	8.355*** (1.074)
Computer accessibility	0.131* (0.066)
Mobile phone accessibility	−0.137 (0.093)
Computer accessibility × mobile accessibility	−0.075 (0.098)
Year × family income group	0.028** (0.011)
Year × economy activity: unemployed	−0.186 (0.132)
Year × economy activity: inactive	0.022 (0.057)
Year × economy activity: not classifiable	−0.587 (0.467)
Year × gender	−0.023 (0.045)
Year × married	−0.008 (0.039)
Year × divorced	0.041 (0.061)
Year × age group	−0.109 (0.096)
Year × percentage of media use time	−2.383*** (0.640)
Year × computer accessibility	−0.028 (0.055)
Year × mobile phone accessibility	0.037 (0.061)
Year × computer accessibility × mobile phone accessibility	0.047 (0.075)
Constant	5.118*** (0.217)
N	9509
Adj. R^2	0.052
F Statistic (df = 23, 9483; 12, 4121)	22.025***

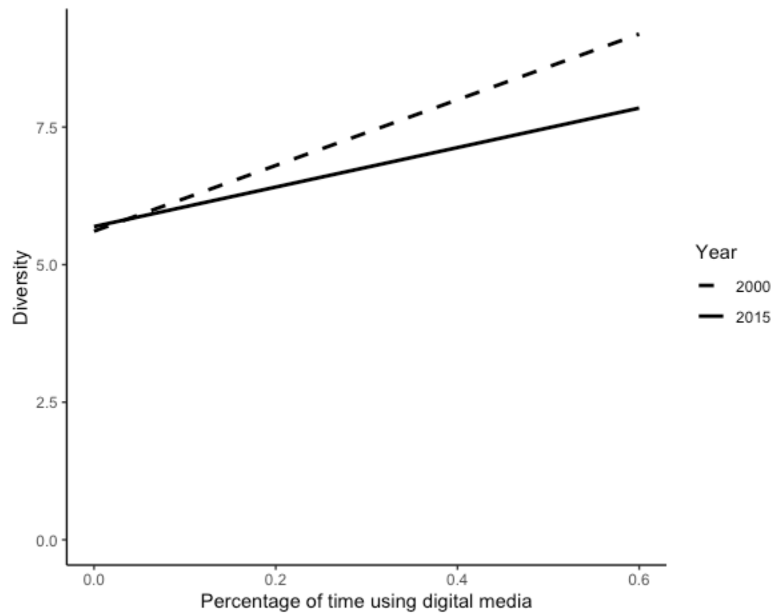

Figure 6. The interaction effect of year and use time on diversity.

Discussion

This study compared the role of digital media access and use in individual daily activities over the years. After controlling for sociodemographics, which were theoretically and empirically significant in differentiating people's lives (Petev, 2013; Vagni, 2020), we found that digital media did affect both interpersonal differentiation and intrapersonal diversification. However, the extent to which these factors were affected was inconsistent considering media accessibility and usage, media modalities, and time frame. In general, computers had a stronger effect compared with mobile phones. Actual media use time had a direct effect compared with media access, and it was more conditional on the time frame.

First, although the effect size was 5% for all the influences, the role of digital media in the organization of daily activities was statistically detectable. People who used digital media had greater differentiation than people who did not use it (H1b). In addition, computer accessibility and actual media use time increased the number of life activities people engaged in during a day (H2). First, this was likely because an online environment helps individuals build new identities and find like-minded people. Second, new norms also emerge with and adapt to digital media devices and online platforms (Baldwin-Philippi, 2012; Zywica & Danowski, 2008). As a result, people who have access to and who use digital media tend to be more different from each other, and their lives more diverse. In addition, the impact was verified across the years. Compared with the year 2000, differences in interpersonal differentiation between levels of digital media accessibility and use were slightly greater in recent years. According to the social acceleration theory (Rosa, 2013), increases in the speed of technological development also accelerate changes in society and increase the pace of life. Considering modality and service development over the past 15 years, digital media are more embedded in modern daily activities. The same media devices are more capable of gratifying people's varied motivations. Thus, different use patterns and skills have unfolded (Friemel & Signer, 2010). These factors have, in turn, led to greater interpersonal differentiation.

Second, we did not detect differences when people had access to one or more digital devices although fundamental differences exist between computers and mobile technologies in function and the technology-life relationship (H3). We also did not detect a shift in which the major media effect role transferred from computers to mobile phones over the years. We can reason that compared with the sociodemographic determinants, the role of digital media in daily activities was relatively small. Interestingly, computer rather than mobile phone accessibility continually played a major role in increasing activity diversity over the years. In 2015, it still enhanced interpersonal differentiation (H4a). This provides evidence of the differential effects of digital media modality on individual activity (i.e., device divide; Tsetsi & Rains, 2017). The innovation of new technology does not necessarily mean that older digital media is becoming outdated. For example, in 2016, people who lacked access to the Internet still regarded a computer rather than a smartphone as their technological preference (Robotham, Satkunanathan, Doughty, & Wykes, 2016). Scholars have suggested that mobile Internet access is an inferior form of access in many aspects, such as content availability and service functionality (Reisdorf et al., 2020). Mobile-only and no-access groups are similar in educational and income levels. They are often considered socially inferior compared with people who can access the Internet using technology that is more capable than mobile devices (e.g., computers; Tsetsi & Rains, 2017). This may be the reason why computer access had a stronger influence than mobile phone access.

Third, digital media increased the differentiation of life trajectories among people, depending not only on the amount of use and the digital media era in which they were embedded, but also on the timing of the activity, as shown in Figure 5. Although media accessibility increased within-person differentiation in the smartphone era, people with high levels of smartphone use were similar to one another in terms of their evening practices. They are likely to prefer similar leisure activities related to media, mainly because digital media displace other home-based activities (Thulin & Vilhelmson, 2006), and evening is normally the primary time available for leisure. This finding can also be attributed to the fact that the lateral (a person's linear day) and vertical (a time point for the entire population) discrepancies represented two types of differentiation. The former indicates how people strategically organize their limited time resources, and the latter is more related to the culturally shared norms of daily activities.

Contributions

This study contributes to the sociology of technology and time. Previous literature has mostly looked into the transformation of life course events and sequences (Brückner & Mayer, 2005; Elzinga & Liefbroer, 2007); this study shows that daily activities also have theoretical implications for understanding social change. In addition, this systematic examination showed the transformation trends of daily rhythms in current society, providing an empirical examination of postmodern transformation. Furthermore, the study postulates explanations for these trends. The social transformation lies in the relationship between technology and life rhythms. Digital media, as a vital object in daily activities, contribute to social change and life pace acceleration. This adds support to the social acceleration theory (Rosa, 2013) and emphasizes the role of digital media in social transformation.

In addition, identifying individual media use rhythms and the media effect on a person's life has distinct contributions to media studies. The results of a systematic comparison of media use and general daily rhythms over the last 15 years indicate that digital media are a driving force of life acceleration, adding new knowledge to the connection between media and society. The results also connect to the literature on mediatization, which describes the role of media in the process of social transformation (Couldry & Hepp, 2013; Schulz, 2004). It should also be noted that this study is one of the first attempts to empirically examine whether and how media and media change work.

The study also shows that a practice perspective and sequence analysis method can be used to explore a wide range of social science questions. A practice perspective provides a proper window through which one can examine theoretical questions without falling into a behavioral context. Although the diary method and behavior logs have long been applied to examine social questions, the sequence perspective provides a new opportunity to quantitatively capture human characteristics at both the holistic and micro levels. This further provides distinct insights for studies on media effect and social change.

In practice, this study confirmed the social meanings of people's temporal rhythms in routine activities. Due to the prevalence of digital media in recent years, personal footprints have become more observable. For information and technology companies and online services, users' timestamps are the most common behavioral log content. Given the knowledge of people's temporal patterns and their social meanings, it is possible to infer online users' backgrounds and the characteristics of society by mining their temporal characteristics. This is of business value because platforms can design more precise advertisements and content recommendations. Policy makers can sensitively detect dynamic social changes. Furthermore, the media effect reminds us to regard media device penetration and digital literacy enhancement as important approaches for improving aspects of life.

Limitations and Implications

However, this study does have several limitations. First, we adopted the classification of daily activity rhythms from the original survey project, which organized individual activities into 10 categories. However, it is possible that digital media use affects some discrete aspects of daily activities and exerts large effects. For example, computer use may affect social and nonsocial leisure differently. It may further displace family life compared with friendship, because young people today typically communicate with friends online. In addition, it is necessary to look at different social groups. Social classes differ in the extent and direction of daily rhythm changes across the years (Petev, 2013; Vagni, 2020). Digital media use may also have a diverse effect on clusters of people. It is worthwhile to study the interactions between social class and media use on the changes in social practice across the years. Second, the findings showed distinct differentiation patterns within a day. It is necessary to investigate the heterogeneity effect at different times of the day and connect this with the social functions of the timing. In addition, although media use and social demographics were included in the model, their explanative power was small. Future studies should explore other explanations of rhythm characteristics.

Although the practice approach provided a meso-level perspective that established a way to quantify cultural change, it is a behavioral paradigm. The practice was affected by structural sources that shaped postmodernity and kept certain steps from postmodernity itself. Future studies should triangulate the findings from a practice perspective with macro-level cultural measures, such as family structure and relations of production. The consistency and differences among them need to be examined.

Third, we only compared two time points: The home computer era and the smartphone era. In 2001, a large number of people in the United Kingdom were already using a home computer. Furthermore, a scope of 15 years might have limited the social changes that we could observe. Thus, it would be better to adopt a time point without computer use as a naturally divided comparison group. This could help in fully observing the effects of digital media and understanding social change. It is also possible to add future observations using the same instruments. In addition to the reason for adopting a longer observation period, we could have benefited from gathering more data when the media were regarded as an embedded device. Moreover, although the current study looked at two time points across 15 years, the observations were not from the same group of people. It is then necessary to validate our findings with a real longitudinal sample.

Fourth, the study found that digital media affected changing daily activities. In the next step, it may be necessary to connect such changes to physical and psychological factors to see how people deal with such a dislocation of daily rhythm. This could help us fully understand the role that digital media play in daily activities.

We only focused on the accessibility and use of digital media, which are regarded as the first-order digital divide that distinguishes people in terms of whether or not the probability of them using digital media exists (Friemel & Signer, 2010). Therefore, it is necessary to analyze the second-order divide (i.e., skills, literacy, and style of use) in changing people's lives (Friemel & Signer, 2010). This is because, with the integration of media, the fundamental feature that distinguishes individuals is no longer whether they use digital media but how they use it.

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