THE IMPACT OF ICT-USAGE ON THE TEMPORAL FRAGMENTATION OF WORK AND SHOPPING ACTIVITIES

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SAMENVATTING

De invloed van ICT-gebruik op de temporele fragmentatie van werk- en winkelactiviteiten

Een populaire veronderstelling in de hedendaagse sociale wetenschappen luidt dat het internet en andere informatie en communicatie technologieën (ICT) de fragmentatie van dagelijkse activiteiten over tijd en ruimte bevordert, waardoor de grenzen tussen de voorheen gescheiden domeinen van werk, zorg en vrije tijd zouden vervagen. Niet alleen werk kan steeds vaker buiten het kantoor verricht worden, bijvoorbeeld thuis met behulp van een personal computer of in de trein middels een laptop, ook de mogelijkheden voor bijvoorbeeld het winkelen via internet leiden ertoe dat men voor het doen van de boodschappen niet langer per se de deur uithoeft en tevens niet langer gebonden is aan de strikte openingstijden van winkels of overige dienstverleners. De variatie die hierdoor kan ontstaan, kan grote gevolgen hebben voor het werk van vervoersplanologen, onder andere vanwege de huidige verwachting dat de fragmentatie van activiteiten waarschijnlijk zal resulteren in een toename van het aantal files. Een heldere omschrijving van wat fragmentatie is, en hoe het empirisch gemeten kan worden ontbreekt echter tot dusverre. Met als gevolg dat er tot op heden nog nauwelijks empirische bewijzen voorhanden zijn ter onderbouwing van deze veronderstelling. Het doel van dit paper is dan ook tweeledig: (1) het voorstellen van een methode voor het meten van de fragmentatie van activiteiten; en (2) het empirisch bepalen van de mate van temporele fragmentatie en zijn relatie met ICT-gebruik. In het ontwikkelde methodologische raamwerk zijn de drie voornaamste dimensies van fragmentatie opgenomen, te weten: het aantal fragmenten; de verdeling van de grootte van de fragmenten; en de ruimtelijke en temporele configuratie van de fragmenten. Om het ontwikkelde raamwerk te verduidelijken, hebben we het toegepast bij de analyse van drie verschillende activiteiten: werken, het doen van dagelijkse boodschappen en het doen van niet-dagelijkse boodschappen. Hierbij is gebruik gemaakt van bestaande verplaatsingsdagboek gegevens uit de regio Utrecht. Hoewel deze gegevens niet in eerste instantie verzameld zijn voor het meten van fragmentatie en zij dus de nodige beperkingen kennen, zijn de empirische resultaten desondanks veelbelovend en verhelderend: het raamwerk blijkt niet alleen in staat te zijn om de temporele fragmentatie van activiteiten te bepalen, maar is tevens complex genoeg om verschillende niveaus van fragmentatie tussen de drie voornaamste dimensies van fragmentatie te ontwaren.

1. INTRODUCTION

It is commonly believed that, due to developments in information and communication technologies (ICTs), "professional and social relations can be established and maintained almost equally easily over any distance across the globe" (*1*, page 388). Couclelis focuses on the possible individual micro-level consequences this might have and argues that, whereas in the recent past knowing where one was often meant knowing what one was doing, activities seem to be getting less firmly linked to fixed spatial locations and times thanks to recent information and communication technological innovations (*1*-*4*). As a result, "activity may be fragmented into tasks that are widely distributed over space and across time" (*4*, page 346). This so-called 'fragmentation of activity' concept is closely related to the notion of a 'blurring of boundaries' between the work, domestic and other spheres of everyday life (*5*-*6*). For instance, work activities used to be rather strictly separated in time and place from maintenance or leisure activities, but the increased opportunities of working from home might result in more interference of other kinds of activities with paid work activities (and vice versa).

The fragmentation of activity is foreseen to have considerable impacts on the work of transportation planners. The predicted increases in travel demand that may result from activity fragmentation may increase road congestion across time (especially during what are now considered non-peak hours) and space (new bottlenecks in addition to existing ones). To assist transportation planning, more knowledge is required whether activity fragmentation takes place and in what ways. Although activity fragmentation as a concept is intuitively sensible it is also difficult to grasp methodologically and empirically, which might explain why until now hardly any empirical research has been done on the subject. There is not only a lack of appropriate data, but also of a clear framework for analysing and measuring fragmentation. A first attempt to measure fragmentation empirically has been made by Lenz and Nobis (*7*). Although these authors find some evidence of the *occurrence* of activity fragmentation, their research does not provide a detailed insight into *the ways in which* activities are fragmented. Transportation planners need to know for instance the number of tasks an activity is divided into and the number of different locations that are visited for these tasks, since different numbers might have very different consequences on related travel behaviour.

To fill the methodological and empirical gap identified above, we present a framework for measuring activity fragmentation and apply this to existing travel diary data. With these analyses we intend to give a preliminary view of the relation between ICT usage (for instance e-shopping) and activity fragmentation. Since no measures have yet been proposed for activity fragmentation, an interdisciplinary approach is employed to identify useful indicators utilized in other disciplines. The selected measures will be presented in section 3. Sections 4-5 introduce the empirical analysis in which we describe the fragmentation for paid work and shopping for daily and non-daily goods and assess whether fragmentation varies systematically with ICT usage. Note that the analysis in the current paper will be confined to the fragmentation of activities across time, as our data do not yet allow us to investigate the spatial dimension of activity fragmentation. The paper ends with a conclusions and discussion section.

2. AN INTERDISCIPLINARY APPROACH TO FRAGMENTATION

2.1. What is Fragmentation?

To prevent us from re-inventing the wheel, we have taken an interdisciplinary approach to find out in what ways processes of fragmentation have been investigated and especially measured in other research areas. A literature survey shows that fragmentation has been studied for a great variety of topics in the fields of sociology, economics and computer science (*8-15*) and that it is a process that can occur for practically every divisible phenomenon or object. Ecology is nonetheless the discipline contributing the most relevant insights for our study: a vast literature exists on the topic of forest and ecosystem fragmentation, what different dimensions of fragmentation can be distinguished and how to measure these processes (*16*). However, while fragmentation has been studied in many research areas, each discipline employs its own specific definition to the concept. As a consequence, there is no unequivocal definition of fragmentation. After Couclelis (*17*, page 11), in this study we define fragmentation as a process whereby:

"activities in the age of ICT are increasingly likely to be disaggregated into their component sub-tasks, each of which may be carried out at or from a different place and at a different time, either physically or remotely, and in several possible sequences".

This paper distinguishes between two kinds of activity fragmentation: *spatial fragmentation* – different places at which the sub-tasks are carried out – and *temporal fragmentation* – different times at which the sub-tasks are carried out. Since the data that we have at our disposal measures activity types using very rough categories, we miss the required level of detail to address the sequencing of activities. The following section introduces three dimensions of fragmentation that have come to the fore in the interdisciplinary literature search that, combined with the distinction between spatial and temporal fragmentation, form the basic structure of our fragmentation concept.

2.2. Dimensions of Fragmentation

We will first address the aspects of fragmentation that are recognized in most disciplines mentioned earlier as constituting distinctive dimensions of fragmentation. Figure 1 introduces the dimensions for temporal and spatial fragmentation separately. The most commonly identified dimension is the *number* of fragments or segments in which a given object (activity, forest or hard disk) is divided (*11-12*, *16*). Rutledge (*16*, page 7) gives a simple but telling example: “A plate that is broken into 100 pieces is more fragmented than a plate broken into 10 pieces.”

The second dimension concerns the *distribution of sizes* of the fragments. As Rutledge (*16*, page 7) continues: “Similarly, a plate broken into 10 pieces of equal size is more fragmented than a plate broken into 10 pieces, one of which is 90% of the original plate.” This is also recognized in the other research areas. Investigating the fragmentation of paid work activities, Mark et al. (*13*) state that work is more fragmented if the amount of time one spends on a task is shorter. Further, sociologist Sullivan (*12*) points at the relation between having long instead of short episodes of leisure time and the experience of time pressure. Longer continuous episodes of leisure time are said to be related to less time pressure than shorter episodes of leisure time, even when the total leisure time on a given day is exactly the same.

Finally, the *configuration* of fragments is considered an important dimension of fragmentation in ecology (*16*). Studying the configuration of activity fragments can provide valuable insights to transportation planners into the pattern formed by the different activity episodes. For instance, if the activity of daily shopping gets temporally fragmented in that people for some reason start making more shopping trips in a day, the outcome of this temporal reordering will be more problematic if some of these shopping episodes are shifted from non-peak to peak hours. Furthermore, if only one episode is moved to a heavily congested moment, the outcome will be less problematical then when several episodes are moved to already congested moments. Configuration is therefore not only concerned with the location of the activity episodes, but also with the distances between the episodes, both in a spatial and in a temporal sense. An object that is divided into different segments can be considered more fragmented if individual segments are more spread out across time and/or location than if concentrated spatially and/or temporally. Thus, a work activity divided into several fragments all executed in the morning is less fragmented than a work activity consisting of the same number of fragments but instead performed in the morning, afternoon, and evening. It does not suffice, however, to consider only the average distances between fragments. This would only reveal the amount of global clustering of an activity (are fragments at the level of the total pattern located relatively nearby or far away) and would lead to the conclusion that pictures B, C and D in Figure 1 portray similar configurations though this is obviously incorrect. It is also relevant to study the possible occurrence of local clusters (several smaller subgroups of fragments within the total pattern, located at a certain distance from one another) or outliers (single cases that are separated relatively far from the other cases) as shown in pictures D and E.

3. FRAGMENTATION INDICES

This section introduces the measures developed for measuring each dimension of activity fragmentation. Most of the measures are based on the literature in ecology and sociology (e.g. *11-13, 16*). Although the empirical analysis below will be limited to temporal fragmentation, the measures for spatial fragmentation will also be discussed. Details on the exact definitions of the measures are available in Table 1.

3.1 Number of Activity Episodes/Locations

This dimension is used to make a first and simple distinction between more or less fragmented activities by counting the number of different episodes of a certain activity in a day (temporal fragmentation) and the number of locations that have been visited in order to carry out this certain activity (spatial fragmentation). The interpretation of this measure is straightforward: the greater the number, the greater the fragmentation.

3.2 Distribution of Sizes

Three measures will be used to determine the distribution of the sizes of the fragments:

1. The mean size of the different fragments an activity is divided into;
2. The standard deviation of the fragments, and;
3. The size of the largest fragment.

Since the mean is sensitive to outliers and very different fragment combinations can have an identical mean fragment size, we will also look at the size of the largest fragment and the standard deviation of the fragment sizes. A small standard deviation and small size of the largest fragment indicate that the fragments are more equal in size and therefore more fragmented. It is expected that the mean size of the fragments and the size of the largest fragment are inversely related to the number of fragments. This would be in accordance with the work of Kitamura et al. (*18*) who found that the number of episodes in a daily activity pattern and the duration per episode are negatively correlated.

3.3 Configuration

The configuration indicators measure whether a certain activity is more or less spread across time and space and in what way. Their value primarily lies in their ability to describe *how* a certain activity is fragmented. As shown in the previous section, this exercise is only fruitful when the indicators enable one to distinguish between potential global and local clustering. Four indicators have therefore been developed:

1. The mean distance between the fragments;
2. The standard deviation of the distances between the fragments;
3. The mean distance from one fragment to its nearest neighbouring fragment; and
4. The standard deviation of the distance to the nearest neighbouring fragment.

The mean distance between the fragments in a temporal sense, hereafter called the mean inter-episode duration, measures the time intervals between each episode and all other episodes. If there are more than two episodes, say three, the duration between the first and third episode is calculated by subtracting the starting time of the third from the ending time of the first episode and discounting the duration of the second episode in-between. With respect to the spatial configuration, the distances between locations can be computed rather easily with a Geographic Information System (GIS), if the data are geocoded.

The use of the four measures discerned here enables us to detect various different kinds of configurations. Table 2 offers an overview of how fragmentation patterns can be represented by the different combinations of mean inter- and nearest episode durations and their standard deviations.

4. DATA AND ANALYSES

4.1 Data Description

The data used for the empirical analysis were originally gathered to examine the relationships between e-shopping and in-store shopping (*19*). It consists of a shopping questionnaire and a two-day travel diary and was collected November-December 2003. The diaries were completed on a Friday and Saturday. It is important to notice that non-Internet users were excluded from the study, rendering it impossible to compare Internet users and non-Internet users in our study. Due to the thorough measurement of the frequency of Internet use, we are nonetheless capable of comparing frequent with infrequent Internet users. The selection of the research area was based on the degree of urbanization and shop-availability levels of residential areas. It consisted of four municipalities located in the heart of the Netherlands: Utrecht (270 243 inhabitants and a high level of shop availability); Nieuwegein (61 806 inhabitants, low level of shop availability and located 7 kilometres from Utrecht); Culemborg (26 613 inhabitants, high level of shop availability and located 17 kilometres from Utrecht); and Lopik (13 869 inhabitants, low level of shop availability and located 18 kilometres from Utrecht). 826 Respondents completed both a shopping questionnaire and a travel diary, of whom 44 percent participated online, and the rest using paper-and-pencil surveys. There appears to be some selection bias in that highly educated persons, females and older persons are over-represented. Further information about the data collection process is available in Farag (*19*).

We have selected this data set because it allows us to assess the fragmentation of activities within daily activity patterns and its association with ICT use. However, the data also has serious limitations. The main limitation lies in the fact that the categorization of activities is too rough to be able to discern possible sub-tasks. For example, the shopping activity can be divided into the sub-tasks of searching for product information, the purchasing of the product, and possibly the returning of the purchased item if it does not meet ones demands after all (*20*). Furthermore, since we only have diary information for two days it is impossible to examine fragmentation in the longer term. Therefore we are unable to determine whether activity patterns that appear to be highly fragmented on a daily level are in fact highly routinized on a weekly or monthly level. We believe, however, that these limitations are more likely to result in an underestimation rather than an overestimation of the extent of activity fragmentation.

4.2 Operationalisation of Variables

In the travel diaries the respondents were asked to fill in the destination type of every single trip they made. For the current analysis, the activity daily shopping was operationalized by selecting the three following destination types: market, supermarket and a combined category that contained the bakery, the greengrocery, the butcher's store and the fish store. Non-daily shopping is made up by the following ten categories: stores for clothing/footwear; domestic appliances; electronics; books; music; computer hard- and software; and toys. Travel agencies; department stores; and drug stores were also included in the non-daily shopping category. The activity work only includes visits to workplaces.

A possible determinant of fragmentation, ICT usage, has been operationalized by recoding the original indicator of ICT usage into a dichotomous variable by labeling respondents that use the Internet at least once a day as frequent Internet users, and the rest as infrequent users.

5. RESULTS

A comparison of the mean scores on the different fragmentation measures gives a first impression of the insights the application of the proposed framework generates. First the differences in activity fragmentation between the three activity types work, daily and non-daily shopping will be presented, followed by a discussion of the differences in the amount of fragmentation in paid labor, daily and non-daily shopping for frequent and infrequent Internet users.

5.1. Activity type

Based on the mean indicator values for the dimensions of the number of activity episodes and the distribution of episode sizes (Table 3), non-daily shopping appears to be the most fragmented activity of the three activity types considered. Not only does the activity of non-daily shopping consist of more different activity episodes than do paid labor and daily shopping (NAE), but these episodes also last shorter (MES) and are more equal in size (SD MES & LEI). As expected, the number of episodes is lowest and the duration per episode longest for paid labor. The average of 1.33 episodes nonetheless indicates that a sizable proportion (42 percent) engages in paid labor more than once per day. The results further show that the expected inverse relation between number of fragments and the duration per episode does not hold when daily and non-daily shopping are compared. This indicates that, as expected, the total time budget for non-daily shopping once engaged in this activity is longer than for daily shopping.

The configuration of the activity episodes measures provide information on the pattern formed by the activity episodes. Do episodes succeed one another rapidly, forming clusters, or are they spread more evenly across the day? According to the mean inter-episode duration (MIED) the time-spans between daily shopping episodes are the longest, namely one hour and forty minutes on average, which is somewhat surprising, since it would appear to be more efficient to chain these different daily shopping episodes together, for instance by letting a trip to the bakery be followed by a trip to the butcher's shop. Perhaps the large MIED for daily shopping is a result of the long opening hours of supermarkets that allow one to do some groceries during the lunch break and do the remaining groceries in the evening after work. The long inter-episode durations may also reflect that needs for (certain) daily products manifest themselves at different moments during the day. The short MIED of forty-two minutes for non-daily shopping might be caused by the possibility that non-daily shopping episodes are often chained together.

It is noteworthy that the MIED and the mean nearest-episode duration (MNED) for paid labor and daily shopping are quite similar. This is because the vast majority of respondents participate in these activity types at most twice per day, in which case the MIED and the MNED are the same. When the activity on average consists of several episodes, as is more frequently the case with non-daily shopping, the combination of the MIED and MNED can provide insight into whether and how these episodes are spread across time, and in the current case, across the day.

Since the MNED for non-daily shopping is lower than the MIED, there is reason to believe that some episodes have a shorter inter-episode duration than others, thereby forming one or more clusters. This claim is substantiated by the standard deviations of the MIED (SD MIED) and MNED (SD MNED). Since both are rather high for non-daily shopping, we can conclude that non-daily shopping episodes form different clusters and that the inter-episode durations are smaller in one cluster than in the other.

In order to be able to compare the configurations of the activity episodes of paid labor, daily- and non-daily shopping, we have corrected for the standard deviations for differences in mean durations of the three activity types by calculating the coefficient of variation (c_v, results not shown here). Since paid labor has the lowest c_v scores, this in combination with the other results tells us that paid labor is rather clustered, given the rather low MIED compared to daily shopping. Non-daily shopping episodes are also more clustered than daily shopping episodes, but the inter-episode durations vary more in size than those of paid labor. Daily shopping episodes appear to have the largest time intervals between episodes, which in combination with the considerable variation in the inter- and nearest episode durations seems to be indicative of the existence of local clusters in combination with an outlier. These differences seem to reflect different time frames for the three activity types. While paid labor is still mainly done between 9:00 AM and 6:00 PM (*21*), store hours are more extended, enabling more variation in the timing of these activities.

5.2. Internet Usage

The differences between frequent and infrequent Internet users (Table 4) are not as expected. Frequent ICT usage does not seem to be related to more fragmented work or shopping activities as reported in the travel diaries. No statistically significant difference exists between frequent and infrequent Internet users in the number of activity episodes. Of all the indicator values for the distribution of episode sizes, the largest episode index (LEI) is the only one approaching statistical significance, indicating that the share of the largest episode is smallest for frequent Internet users. In this sense, paid labor is slightly more fragmented for frequent Internet users than for infrequent Internet users.

The temporal configuration of the activity episodes does appear to differ according to the frequency of Internet usage. The mean inter- and nearest episode durations for paid labor and daily shopping are on average 15 minutes shorter and therefore more clustered for frequent than for infrequent Internet users. Due to the small number of cases these differences are not all statistically significant. For the same reason the substantial dissimilarities in inter- and nearest episode standard deviations (SD MIED and SD MNED) are not statistically significant either, though they suggest considerably more variation in the between-episode time intervals among frequent Internet users. The combination of large values for the SD MIED and high SD MNED for daily shopping suggest a pattern of shopping episodes containing an outlier for frequent Internet users. This might reflect that they shop in the evening hours more often than do infrequent Internet users. This same line of reasoning might also apply to the non-daily shopping of frequent Internet users which similarly portrays high standard deviations in the configuration dimension.

6. CONCLUSIONS AND DISCUSSION

This paper had a double goal: proposing a methodology for measuring activity fragmentation; and assessing temporal fragmentation empirically and consider its association with ICT usage. A methodological framework has been proposed built around three dimensions of fragmentation: the number of fragments; the distribution of the sizes of fragments; and the spatial and temporal configuration of fragments. The application of this framework to existing travel diary data has demonstrated its suitability for studying activity fragmentation processes. This is because the framework is capable of distinguishing between more and less fragmented activities and describing differences in the configuration of the fragments. Further, by allowing comparisons across dimensions, the framework enables the location of other causes of fragmentation in ways that would have been impossible when concentrating only on the individual dimensions separately (results not shown here). These insights could not have been gained by only concentrating on the individual dimensions. More generally, the preliminary analysis reported here has not generated convincing evidence that Internet use encourages activity fragmentation.

It cannot be overemphasized, however, that the empirical analysis should be considered illustrative for several reasons. First, only temporal fragmentation has been considered, rendering the possibility of different conclusions had the framework been employed to study spatial fragmentation. Second, the bivariate nature of analysis reported here renders it impossible to determine whether the differences in the temporal fragmentation of activities are confounded by the impact of other factors. Subsequent research should therefore employ multivariate statistical analysis.

Third, the analysis is limited because of various inherent limitations of the applied data. The collection of data specifically tailored to the study of activity fragmentation is warranted. These data should meet the following requirements. First of all, the data should enable the analyst to make more subtle distinctions between activity types – for instance by allowing non-daily shopping to be divided into shopping for non-daily search or experience goods. The data should also enable the analysis of the series of acts that constitute a given activity because the fragmentation hypothesis holds that these acts may be distributed across space and time more easily through ICT use. Thus, the general activity of shopping should be unravelled into the sub-tasks of searching for product information, the purchasing of the product, and possibly the returning of the purchased item if it does not meet ones demands after all (*20*). Furthermore, the data should also allow a distinction between primary and secondary activities. Otherwise, when a person for instance works while travelling home by train, and commuting is the primary activity, the secondary work activity would not be detected. Finally, further enrichment of the data could be brought about by expanding the time scale of the data from the two days of the current paper to preferably several weeks (*22*).

The framework proposed in this paper may also be improved and extended in future research. For instance, the simplifying assumptions that were made about the possible relations between the different types of activities, the time of day dependency, and the relations between the activity patterns of different household members (Section 2.2) could be relaxed. It is also important to address concepts that are intimately associated with fragmentation but could not be addressed in this paper. Especially for informing policymaking, future research should be able to provide insights into the norms about, and evaluations of, activity fragmentation. After all, the technical feasibility to be able to fragment activities does not guarantee that people will actually do so. If people evaluate fragmentation negatively, they are probably less prone to fragment their activities, and futuristic views of highly fragmented daily activity patterns will never actualize.

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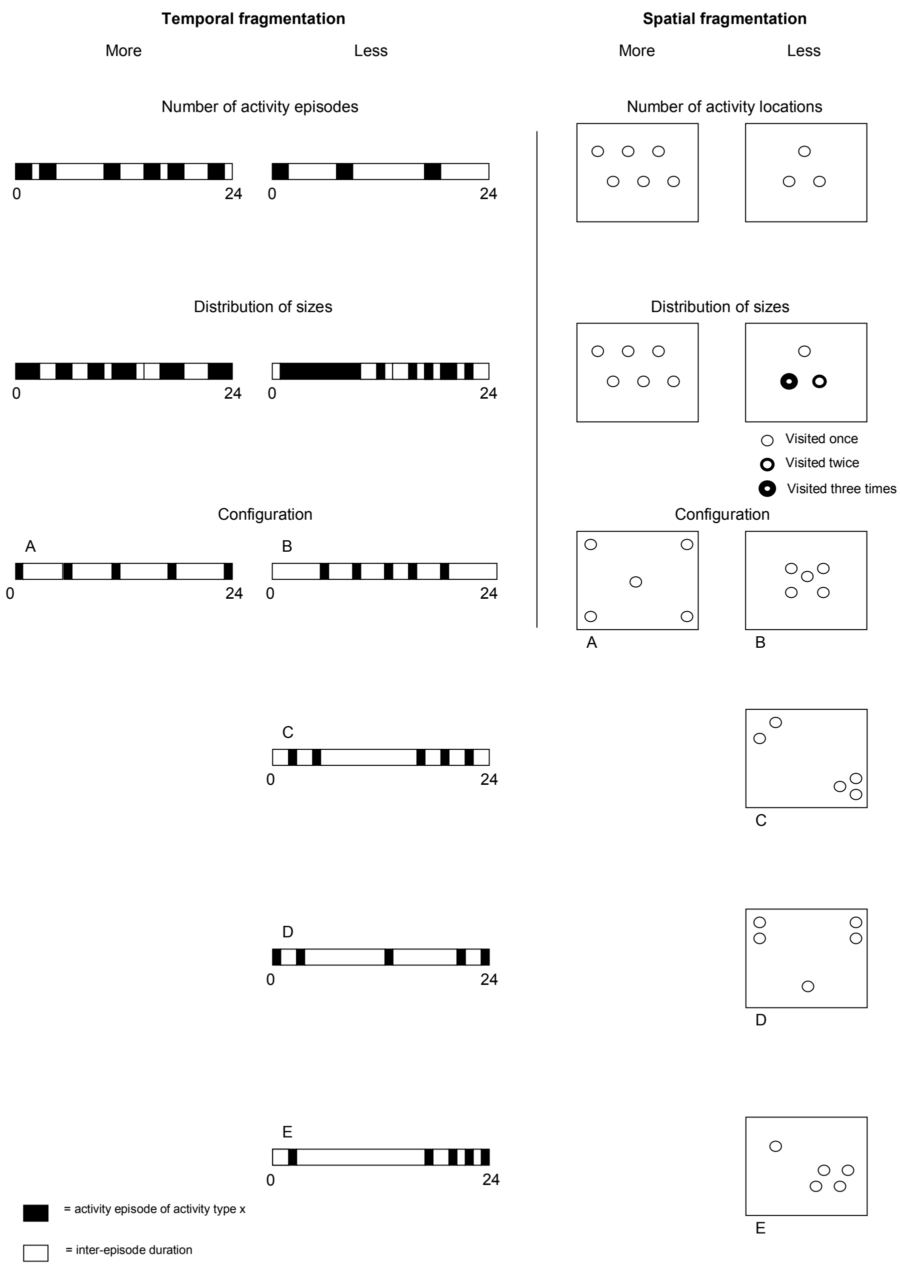


FIGURE 1 Three dimensions of fragmentation.

TABLE 1 Description of Configuration Measures

	Temporal fragmentation			Spatial fragmentation		
	Name	Symbol	Description	Name	Symbol	Description
Number	Number of activity episodes	NAE	Counts the number of activity episodes	Number of activity locations	NAL	Counts the number of unique activity locations
Distribution	Mean episode size	MES	Divides the total activity duration by the number of activity episodes. Results are always larger than 0	Mean location weight	MLW	Divides the number of unique activity locations by the number of activity episodes. Result can lie between 0 and 1 with 1 indicating that for each activity episode a different location is visited
	Mean episode size variance	SD MES	Calculates the variance of the episode durations	Mean location weight variance	SD MLW	Calculates the variance of the location weights
	Largest episode index	LEI	Divides the episode with the longest duration by the total activity duration and multiplies it by 100	Largest location index	LLI	Divides the location that is visited most often for a certain activity by the total number of unique activity locations and multiplies it by 100
Configuration	Mean inter-episode duration	MIED	Divides the sum of all inter-episode durations by the number of inter-episode durations	Mean inter-location distance	MILD	Divides the sum of all inter-location distances by the number of inter-location distances
	Mean inter-episode duration variance	SD MIED	Calculates the variance of the inter-episode durations	Mean inter-location distance variance	SD MILD	Calculates the variance of the inter-location distances
	Mean nearest-episode duration	MNED	Divides the sum of all nearest-episode durations by the number of nearest-episode durations	Mean nearest-location distance	MNLD	Divides the sum of all nearest-location distances by the number of nearest-location distances
	Mean nearest-episode duration variance	SD MNED	Calculates the variance of the nearest-episode durations	Mean nearest-location distance variance	SD MNLD	Calculates the variance of the nearest-location distances

TABLE 2 Fragmentation Patterns and their Indicator Values

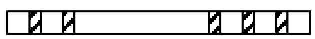
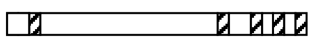
Temporal fragmentation pattern	Indicator values		Description of fragmentation pattern
 0 24	MIED SD IED MNED SD NED	high low high low	Spread evenly
 0 24	MIED SD IED MNED SD NED	low low low low	Global clustering
 0 24	MIED SD IED MNED SD NED	high high low low	Multiple local clusters
 0 24	MIED SD IED MNED SD NED	high high high high	Multiple local clusters and an outlier
 0 24	MIED SD IED MNED SD NED	low medium medium medium	Global cluster and outlier

TABLE 3 Fragmentation of the Activity Types Paid Labor, Daily and Non-Daily Shopping

		Number of activity episodes	Episode size Distribution			Configuration of activity episodes			
		NAE	MES	SD MES	LEI	MIED	SD IED	MNED	SD NED
Paid labor	Mean	1.33	354.8	96.8	91.5%	54.7	30.7	48.8	12.7
	N obs.	409	409	93	409	93	24	93	24
Daily shopping	Mean	1.43	27.7	12.8	89.8%	101.7	66.9	90.2	52.2
	N obs.	625	625	196	625	196	52	196	52
Non-daily shopping	Mean	1.95	27.3	11.1	80.1%	42.5	37.6	28.8	26.4
	N obs.	384	384	175	384	175	94	175	94

TABLE 4 Comparison of Activity Fragmentation of Infrequent and Frequent Internet Users

		Number of activity episodes	Episode size Distribution			Configuration of activity episodes			
		NAE	MES	SD MES	LEI	MIED	SD IED	MNED	SD MNED
Paid labor									
Infrequent	Mean	1.28	361.4	94.6	93.3%	70.0	37.9	61.0	6.6
	N obs.	163	163	30	163	30	8	30	8
Frequent	Mean	1.35	350.4	97.9	90.3%	47.5	27.2	43.0	15.7
	N obs.	246	246	63	246	63	16	63	16
	p-value [a]	*.361*	*.537*	*.880*	*.077*	*.085*	*.401*	*.154*	*.327*
Daily shopping									
Infrequent	Mean	1.46	28.3	13.1	88.8%	111.0	50.3	102.6	36.4
	N obs.	262	262	91	262	91	23	91	23
Frequent	Mean	1.42	27.3	12.5	90.6%	93.6	80.1	79.5	64.7
	N obs.	363	363	105	363	105	29	105	29
	p-value [a]	*.500*	*.639*	*.734*	*.203*	*.282*	*.079*	*.149*	*.073*
Non-daily shopping									
Infrequent	Mean	1.94	26.1	10.1	81.2%	42.6	26.6	31.2	20.7
	N obs.	150	150	63	150	63	42	63	42
Frequent	Mean	1.96	28.0	11.7	79.4%	42.5	46.5	27.5	30.9
	N obs.	234	234	112	234	112	52	112	52
	p-value [a]	*.883*	*.602*	*.329*	*.488*	*.987*	*.079*	*.665*	*.313*

[a] *p*-value for a *t*-test for the difference in averages for infrequent and frequent internet users