Journal of Transport Geography 18 (2010) 55–64

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

Fragmentation of work activity as a multi-dimensional construct and its association with ICT, employment and sociodemographic characteristics

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ARTICLE INFO

Keywords:
Work activity
Information and communication technology (ICT)
Fragmentation

ABSTRACT

A potential effect of ICTs is that they alleviate the traditional space-time constraints of paidwork activities and allow for the decomposition of work into multiple segments of subtasks, which can be performed at different times and/or locations. Such separation of activities into discrete pieces is commonly termed the fragmentation of activity. Regrettably, only limited empirical evidence is available on the fragmentation of work activity and the factors that contribute to it. The goal of this paper is to extend the previous work in the activity fragmentation arena in three ways: (i) to operationalize measures of spatial fragmentation and reformulate some of the temporal fragmentation measures for the specific purpose of investigating the fragmentation of the work activity; (ii) to analyse fragmentation not only in terms of the individual indicators, but also as a multi-dimensional construct including all dimensions of spatial and temporal fragmentation collectively; (iii) to test a detailed set of ICT-related, workrelated, and sociodemographic variables to identify the factors that are crucial in the occurrence of the fragmentation of the work activity. The study shows that there is heterogeneity in the fragmentation of work. Three internally homogenous patterns of fragmentation, which diverge in the degree of fragmentation, are identified: (1) a less temporally and spatially fragmented work pattern; (2) a less spatially and more temporally fragmented work pattern; (3) a more spatially and temporally fragmented work pattern. The multiple discriminant analysis suggests that ICT variables and work-related variables as well as personal-household attributes are associated with the fragmentation of work. However, the degree of association differs considerably among representative patterns of fragmentation.

1. Introduction

It is a common belief that the advancement of modern information and communication technologies (ICTs) such as broadband and mobile internet connection, phone, and laptop has brought changes in the way business is conducted and work is done. New forms of working such as telecommuting, part-day home-working, commuting-based and mobile-based work have already emerged (Pendyala et al., 1991; Mannering and Mokhtarian, 1995; Koenig et al., 1996; Vilhelmson and Thulin, 2001; Lyons and Haddad, 2008). A potential effect of ICTs is that they alleviate the traditional space-time constraints of paid work activities and increase the range of locations and times available for conducting these activities (Couclelis, 2000; Dijst, 2004). For instance, work can be transferred more easily from the workplace to the home (using a wired telephone and internet) or while travelling (using a mobile phone or laptop computer with wireless internet connections). This relaxation of spatial and temporal constraints allows for the decomposition of work into multiple segments of subtasks that can be performed at different times and/or locations. Such separation of activities into discrete pieces is commonly termed the fragmentation of activity (Couclelis, 2000).

ICT and the fragmentation of work activities potentially have an impact on the use of the daily urban system in terms of the intensity and timing of the use of facilities and transport infrastructure. For instance, telecommuting might lead to a decrease in the frequency of commuting. Similarly, the spatial fragmentation of work activities may lead to an increase in travel distances. Activity fragmentation has furthermore been predicted to result in increased travel demand and, although traffic during conventional peak hours might be relieved, increased road congestion during what are now considered non-peak hours might ensue. New traffic bottlenecks might also evolve. More dynamic and fragmented activity-travel patterns may reflect changes in people's preferences resulting, for example, in new requirements for dwellings (with preferences possibly changing from living near the main employment location to living close to recreational facilities), workplaces (with flexible workstations), and public transportation (with broadband wireless Internet access in both train stations and the trains themselves) (Alexander et al., submitted for publication). It is therefore essential for urban and transport planners to know

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doi:10.1016/j.jtrangeo.2009.05.010

how, to what extent, and in what manner urban structure and mobility are affected by ICT and fragmentation. However, before exploring these issues we need to develop an understanding of the impact of the availability and use of ICT on fragmentation.

To date, limited empirical evidence is available on the fragmentation of work activity and the factors that contribute to it. Using a one-day activity diary, Lenz and Nobis (2007) found that work activity is more likely to be fragmented as a result of ICT. However, it is unclear in this study how the work activity is fragmented and how the fragmentation is measured. Hubers and colleagues (2008a) made the first attempt to measure activity fragmentation by proposing three dimensions: the number of fragments, the distribution of sizes of the fragments, and the configuration of the fragments. Although these three dimensions offer a comprehensive picture of how, in what way, and to what extent activities are fragmented, they were not analysed simultaneously and spatial fragmentation was neglected. In addition, a limited set of determinants of fragmentation was tested.

The current study extends the previous work in the activity fragmentation arena in three ways. First, we operationalized measures of spatial fragmentation and reformulated some of the temporal fragmentation measures for the specific purpose of investigating the fragmentation of the work activity. Second, we analysed fragmentation not only in terms of the individual indicators, but also as a multi-dimensional construct including all the dimensions of spatial and temporal fragmentation collectively. Third, we tested a detailed set of ICT-related, work-related and sociodemographic variables to identify the crucial factors in the occurrence of fragmentation of the work activity.

To address these issues, we first derived a series of temporal and spatial fragmentation measures using a dataset collected in the in the central part of the Netherlands. These measures (Alexander et al., submitted for publication) were then used simultaneously as input of a clustering algorithm, in order to determine a number of typical fragmentation types. Finally, we examined whether different aspects such as ICT possession and use, work, personal, and household-related attributes are associated with the patterns of work activity fragmentation.

The remainder of this paper is organized as follows. In Section 2, we discuss the concept of fragmentation. A review of time use and travel studies follows, leading to hypotheses with respect to the key factors of the temporal–spatial fragmentation of work activity. The research design and methodology are explained in Section 3. In Section 4, we present the empirical results of our analysis; in Section 5 we put forward our conclusions and suggest avenues for further research.

2. Theoretical framework

2.1. The concept of "fragmentation"

The concept of the fragmentation of activities has received considerable attention in recent years. The concept was initially proposed by Couclelis (2003) to assess how activities are reorganized in time and space as a result of ICT use. She described fragmentation in the following terms: "*fragmentation is a process whereby a certain activity is divided into several smaller pieces, which are performed at different times and/ or locations*" (Couclelis, 2003, p. 11).

Hubers and colleagues (2008a) distinguish two kinds of activity fragmentation. Temporal fragmentation refers to activities carried out at different times, while spatial fragmentation relates to activities carried out at different places. In addition, we developed three dimensions in this study to investigate how activities are fragmented temporally and spatially: the number of fragments; the *distribution of the size of fragments;* and their configuration.

For example, a work pattern consisting of 10 episodes is more fragmented than a work pattern divided into only 2 episodes (see Figs. 1a and 2a). Thus, the images on the left are less fragmented then the images on the right. With respect to the second dimension, the images on the right are more fragmented than those on the left. The number of episodes/locations is exactly the same for both; however, the amounts of time spent per episode or location differs. Finally, looking at Figs. 1c and 2c, we see five types of configuration of the fragments, including global clustering, evenly spread, global cluster with outlier, multiple global cluster, and multiple clusters with outlier. We conclude that global clustering is less fragmented than evenly spread images. With respect to the spatial fragmentation, Fig. 2c shows differences in the configuration of fragments of activity locations.

Based on these dimensions of activity fragmentation, Alexander and colleagues (submitted for publication) have developed an extensive set of fragmentation measures for each dimension. The specification of the measures used in this study is discussed in Section 3.

2.2. Determinants of fragmentation of work activity

An important objective of this study is to gain insight into the role of ICT in the fragmentation of work activity. In this section, we discuss the potential impact of ICT on activities in order to provide a basis for further empirical analyses. However, since not only ICT, but also work-related and sociodemographic variables may play a role in the scheduling of activities, we also discuss the expected impact of those activities.

2.2.1. ICT-related variables

In recent years, a substantial body of studies has addressed the complex relationship between ICT and daily activities (Handy and Mokhtarian, 1996; Mokhtarian and Salomon, 1997; Hjorthol, 2002; Couclelis, 2000, 2003; Hubers et al., 2008a; Lenz and Nobis, 2007). The theoretical and empirical evidence these studies have provided make it apparent that the adoption of ICTs and their use may be associated with the fragmentation of activities. For example, Lenz and Nobis (2007) found that mobile computer users show fragmentation in all their activities. Using two-day diary data, Hubers and colleagues (2008a) have shown that ICTs are not related to all fragmentation indicators, but only to one or two, most often in a positive way. The empirical result shows that frequent Internet users tend to have more work episodes than infrequent users. These authors argue that the relationship between ICTs and activity fragmentation differs for the kind of ICT and kind of activity investigated.

Another strand of literature has explored how the use of ICTs may not be a personal choice, since employers can require employees to use technology, even outside the office (Chesley et al., 2003). We therefore expected that the financial aspect for internet and mobile use would also be related to the fragmentation of work activity. In addition, recent studies suggest that, with the widespread adoption of information and communication technologies (ICTs) together with an increase in the flexibility of work arrangements, people now schedule their work activities in a more flexible way (Kwan, 2002; Schwanen and Kwan, 2008). Therefore, It can be hypothesised that the employer provides employees with financial support to encourage them to accomplish more jobs; the investment results in temporal and spatial fragmentation. At the same time, we might hypothesise that, given the rapid diffusion of various ICT applications, including mobile phones, laptop computers, and PDAs, work organization promotes the flexibility of work to effectuate working from home and other places.

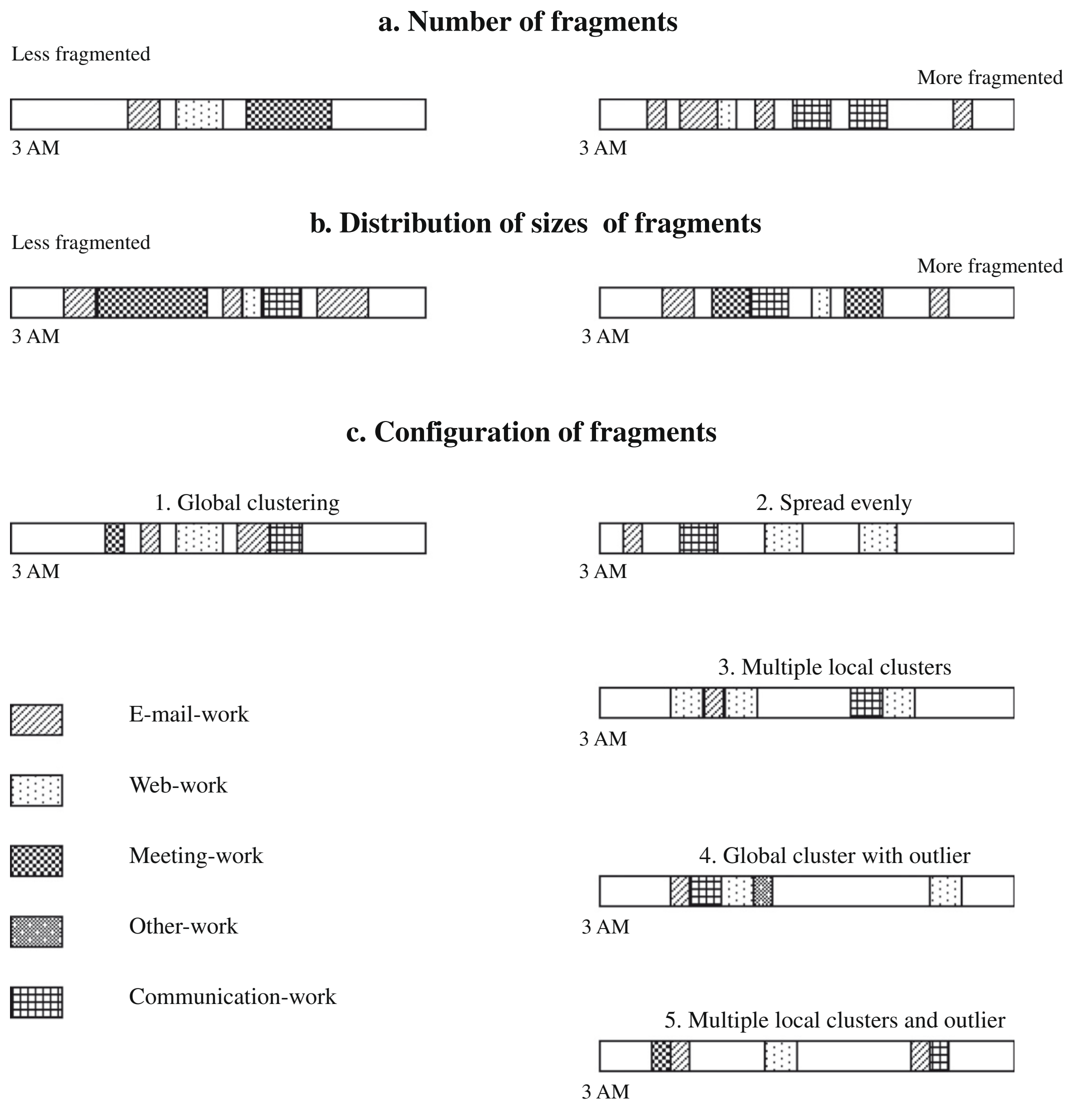

Fig. 1. Dimensions of temporal fragmentation.

2.2.2. Work-related characteristics

Besides using ICTs, we expect that other-work-related factors, including working hours, education level, commute distance, and occupation are also related to the temporal and spatial fragmentation of work. For instance, a person who works more hours will probably experience more fragmented work patterns. On the basis of a Norwegian survey, Hjorthol (2002) found that, for people who work more than the normal weekly hours, stationary technology gives them greater flexibility with regards to where and when they work. Men belonging to higher income groups with high educational levels more often own a home computer and are able to work at home compared with those with lower incomes and educational levels. With respect to commuting distance, her result shows that commute distance has a positive impact on the frequency of teleworking (see also Iscan and Naktiyok, 2005; Helminen and Ristimäki, 2007). Mokhtarian and Salomon (1997), Mokhtarian and Krishna (1998) also show that commuting distances are longer for telecommuters than for regular commuters. Work fragmentation could therefore be expected to increase with commuting distance.

The way work activities are organized in time and space has been subject to change. New organizational demands have led to the rise of the ‘post-modern’ professional (Kakihara and Sørensen, 2002; Kakihara, 2003). Many highly-skilled people are independent and manage their careers, lives, and work in a flexible manner. With the introduction of powerful and affordable personal computers, laptops, internet access, mobile phones, and PDAs, their work practices have become mobile from a *locational* perspective, affecting workers’ geographical movement; in *operational* respects, in relation to their capability for flexible operation working independently; and in *interactional* aspects, which are associated with intense and fluid interaction with a wide range of people (Kakihara and Sørensen, 2004). Using a dataset related to sixty-two professionals in Tokyo, they found dynamic and heterogeneous work practices among mobile professionals. Bearing these points in mind, the fragmentation of work could be expected to differ between employment sectors.

2.2.3. Personal and household attributes

It is a common belief that an increase in the flexibility of the timing and location of work activities offered by ICT has made it easier for employees to combine family and work activities (Toffler, 1980; Chesley, 2005). Previous studies have explored how such personal and household factors as gender, presence of children, household net income, and number of cars in the household potentially have an impact on work activity engagement (Hanson and

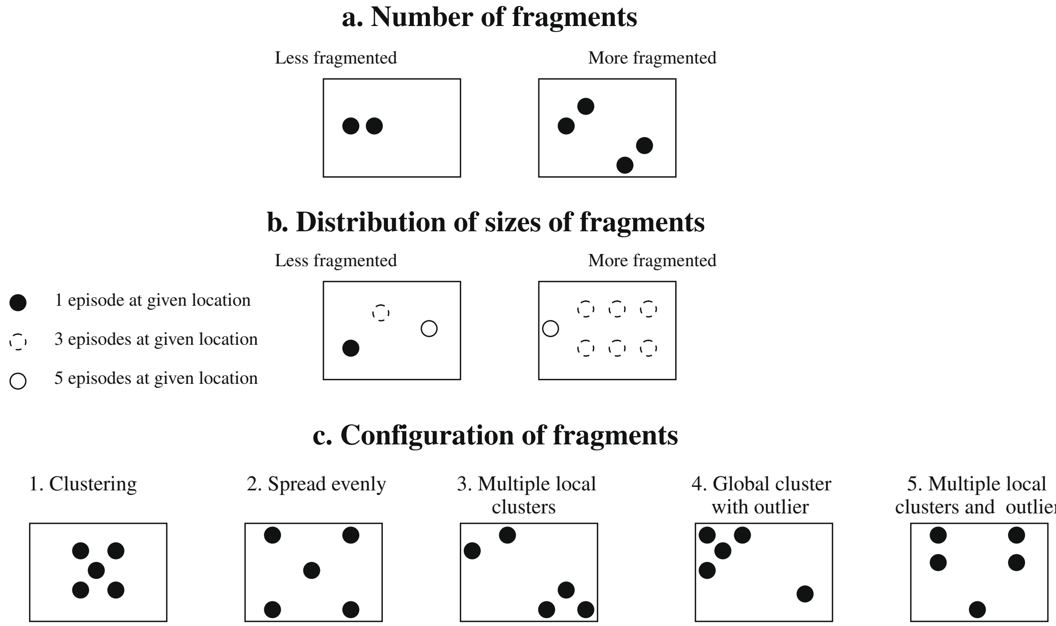

Fig. 2. Dimensions of spatial fragmentation.

Hanson, 1981; Pas, 1984). We therefore expected that these attributes might also be associated with the fragmentation of paid work. There is evidence that men continue to spend more time in paid work than women do and that women continue to spend more time in household chores and caring for children than men do, even when both spouses work (Reskin and Padavic, 1996). This statement leads us to hypothesise that men have more fragmented work patterns than women do. de Graaff and Rietveld (2007) found that individual characteristics (especially age and education) seem to be more important factors influencing the choice between working at home and out-of-home than ICT availability or commuting time. Hubers and colleagues (2008a), for instance, found that age, the presence of children, and education levels have stronger relationships with fragmentation than ICTs do. Chauffeuring in particular has a strong impact on the fragmentation of paid work. The presence of a small child in the household is also known to be related to the arrangement of work activities. For example, an increase in flexible work practices becomes increasingly important in the reconciliation of work and caring responsibilities (Handy and Mokhtarian, 1996). In addition to these personal characteristics, household type and residential location may also affect patterns of fragmentation. People who live in single-person households may have fewer space-time constraints and will therefore have less fragmented work patterns than people who live in households with small children. With respect to residential context, Hubers and colleagues (2008a) found that people living in the suburbs have more working episodes than people who live in other areas.

3. Research design and methodology

3.1. Description of the data

The empirical analyses were carried out with data collected in the Utrecht–Amersfoort–Hilversum region in 2007. This part of the Netherlands is more service oriented and more urbanized than other parts, suggesting that fragmentation might frequently occur. The survey was conducted among single and dual-income households. The collection of data took place in several stages. Initially, selection questionnaires were sent to around 13,500 respondents living in different neighbourhoods in the research area; neighbourhoods were then selected on the basis of a combined income, density, and accessibility matrix. In total, 26 areas were selected, according to income, density, and accessibility levels. In the following stage, we determined the number of addresses to be sampled per neighbourhood; addresses within each neighbourhood were selected randomly using digital files containing all street addresses. The selection questionnaire contained questions about general household characteristics, the possession of ICT devices, and whether the addressee would like to participate in the main survey. Those respondents who were willing to participate in the main survey were sent a questionnaire and a 2-day combined activity-travel-communication dairy. In total, the questionnaire was completed by approximately 740 people, either online or in a mail-out/mail-back paper-and-pencil format. The activity and communication diary was completed by 662 respondents (only paper-and-pencil format). They were asked to complete the details about their activities (the location, start/end times, and with whom). With regard to the ICT questionnaire, the respondents indicated how often they used different types of ICT devices (i.e. landline and mobile phones, PDA, laptop with internet) for work and/or private purposes. With regards to the travel, people were asked to provide us with the origin and destination, type of transport mode, duration, and activity of each trip.

The original dataset was further screened for empirical analysis of the fragmentation of work activity. Individuals who did not engage in working activities during the survey days were excluded from the sample. After the screening process, 528 individuals provided useful information for the analysis and 891 person-days were made available for the empirical analysis.

It should be noted that our the sample slightly overrepresented high-level professionals: 45% of the respondents were highly-educated professionals (scientific, technical, healthcare, ICT, and so forth).

The shares of men and women in the sample are 47.7% and 54.3%, respectively. In terms of working hours, the mean value is 31.86 h per week. However, a considerable difference is observed between men and women: men worked on average 36.31 h per week, while females worked 28.02 h per week.

3.2. Operationalization of variables

3.2.1. Defining work activities

In the current study, work encompasses any kind of paid work ranging from manual labour to knowledge-intensive employment. We distinguish the following subtasks: (EW) email-work, (WW) web-work, (MW) meeting-work, (OW) other-work (reading, writing reports, and so forth) and (CW) communication-work (including communication-work while travelling). It should be noted that work-related emailing only includes the reading of emails and not their composition. As indicated in our data, these subtasks were undertaken at a single (office) or several locations (home, office, train, and so forth). The respondents in the survey were asked to provide us with information about whether they worked during their trip. *Working while travelling* is considered as *working in a non-stationary location*. We derived the subtask of communication-work from the communication section of the diary. The respondents were also asked to report with whom they had communicated. Communication with colleagues or clients was classified as episodes of CW. It should also be noted that EW refers to the reading of emails and not their composition.

3.2.2. Independent variables

Four types of variable are available to examine how they are associated with the fragmentation measures and a number of typical fragmentation patterns: ICT possession; ICT use; work-related variables, and personal-household attributes. With regard to the ICT-related variables, the respondents were asked to report what kind of information and communication devices (laptop, desktop computer, mobile/landline phone, personal digital assistant, and so forth) they possessed and how often they used them for work and private purposes. Our data indicate that a large proportion of the respondents carry mobile phones and the majority of the sample possesses a personal computer at home. According to theoretical and empirical studies (Couclelis, 1998; Kakihara, 2003; Lenz and Nobis, 2007; Hubers et al., 2008a) the mobile phone is strongly associated with the fragmentation of activities. However, mobile phone possession does not differentiate our sample. For our purposes we therefore selected the following variables as ICT possession variables: personal digital assistant (PDA), personal computer with internet, and laptop. With regard to the ICT use variables, we have only used non-work-related ICT use variables as independent variables, because work-related email/web and communication are considered as subtasks of work activity. The choice of the other independent variables was guided by the previous studies reviewed in Section 2.

3.2.3. Measuring fragmentation of work activity

In this section, we report the operationalization of the fragmentation measures. The descriptions of the measures for this study are presented in Table 1. Below are the specifications of measures for the temporal fragmentation and spatial fragmentation of work activity.

According to Hubers and colleagues (2008a), an initial indicator of whether the work activity is more or less temporally fragmented is the number of fragments. Quantification is obtained by counting the number of different episodes of the work activity. The activity episode is defined as *an uninterrupted stretch of time devoted to a certain subtask of work*. For example, in the right image of Fig. 1a, the subtask of email-work consists of four episodes. Let E be the total number of work episodes on a given day. Then:

$$E = \sum_{i=A}^{n} e^i \quad \text{and} \quad L = \sum_{j=1}^{n} l_j \tag{3.1}$$

Table 1
Measures of fragmentation.

Dimension	Measures		
	Symbol	Description	Value
Temporal fragmentation			
Number of fragments	E	A total number of episodes for work activity on a given day	$1 < E < max$[a]
Distribution size of fragments	T_index	Temporal index of fragmentation: to measure how the total number of work episode is fragmented into different tasks	$1/Z < T\_index < 1$
Configuration of fragments	T_{day}	Spread index of work episodes: to measure the dispersion of work episodes across a day	$0 < T_{day} < 12$ h
Spatial fragmentation			
Number of fragments	L	A total number of work locations	$1 < L < max$
Distribution size of fragments	S_index	Spatial Index of fragmentation: to measure the distribution of work episodes across different locations	$1/L < S\_index < 1$
Configuration of fragments	S_{xy}	Spread index of work locations: to measure the dispersion of work locations	$0 < S_{xy} < max$

[a] Max – the high value of the measure.

where i is a subtask of work activity ($i = A, B,.. Z$). For example, work can be decomposed into activities such as meeting, emailing, writing a report, and so forth, and e^i is the number of episodes of the ith subtask of work. L is the total number of activity locations (work locations for the current study) and l_j is the jth activity location. The interpretation is relatively straightforward: a greater number of E (L) indicates more temporal (spatial) fragmentation of paid work.

The next dimension, the *distribution of the size of fragments*, can be measured by focusing on the time spent on each subtask of work. The distribution of the total work duration across different tasks and locations is described as:

$$T = (t^{e_A}, t^{e_B}, \ldots, t^{e_Z}) \quad \text{and} \quad T = (t_{l1}, t_{l2}, \ldots, t_{lL}) \tag{3.2}$$

where: T is the time spent on work activity on a given day; $t^{e_A}, t^{e_B}, \ldots t^{e_Z}$ is the time spent on subtask $A, B, \ldots Z$; t_{l1}, t_{l2}; t_{lL} is the number of episodes at location l_1, $l_{2,\ldots lL}$. The fractions of $t^{e_A}, t^{e_B}, \ldots t^{e_Z}$ and t_{l1}, t_{l2}; t_{lL} are obtained as:

$$P(t^{e_A}) = \frac{t^{e_A}}{T} \ldots \quad P(t^{e_Z}) = \frac{t^{e_Z}}{T} \quad \text{and} \quad P(t_{l1}) = \frac{t_{l1}}{T} \ldots P(t_{lL}) = \frac{t_{lL}}{T} \tag{3.3}$$

The result of the Eq. (3.3) can be used to quantify the second dimension of fragmentation:

$$T\_index = P(t^{e_A})^2 + P(t^{e_B})^2 + \ldots + P(t^{e_Z})^2 \tag{3.4a}$$

$$S\_index = P(t_{l1})^2 + P(t_{l2})^2 + \ldots + P(t_{lL})^2 \tag{3.4b}$$

where: *T_index* is the temporal index of work activity, the measurement of the *distribution of the size of fragments*. For interpretation, we subtract the *T_index* from 1. Thus, a value of 0, indicates that the work activities of an individual on a given day are not fragmented and a maximum value of *T_index* describes more temporal fragmentation of work (an equal allocation of time to all subtasks). *S_index* is the spatial index of work activity and is interpreted in a similar way.

The third measure of temporal fragmentation represents the last dimension, the configuration of the fragments. This measure describes the spread of work episodes across a given day and indicates whether multiple episodes for work activities are concentrated in a certain period of time, the afternoon for instance, or distributed across a whole day. The measure can be defined based on the mean point (MP) of each episode. Suppose that an individual has a certain number of episodes for different work tasks. For a single episode, let S_i and E_i be the start and end times of episode i. Then the MP of episode i can be defined as:

$$M_i = \frac{S_i + E_i}{2} \tag{3.5}$$

where M_i is the MP of the i th episode. For multiple episodes, the MP can be obtained as:

$$\bar{M} = \sum_{i=1}^{n} \frac{M_i}{E} = \frac{M_1 + M_2 + M_3 \ldots M_n}{E} \tag{3.6}$$

where $\bar{M}$ is the MP with respect to multiple episodes; M_1, $M_{2\ldots}M_n$ is the MP for the 1st, 2nd…nth episodes; E is the total number of episodes on a given day. Then the dispersion of the work episodes across a day can be defined by:

$$T_{day} = \sqrt{\frac{\sum_i D_i \cdot d^2_{M_i\bar{M}}}{\sum_i D_i}} \tag{3.7}$$

where T_{day} is the spread index of work episodes, D_i is the duration of episode i (i = 1…n), $d_{M_i\bar{M}}$ is the distance between M_i and $\bar{M}$. If T_{day} takes a value close to 0, it indicates that a work pattern consists of several episodes, which is close to its $\bar{M}$; a larger value of T_{day} then describes a greater dispersion of work episodes across the whole day.

The spatial configuration of the fragments is reflected by a standard distance (Bachi, 1962), which is used to explore the spread of activity locations. The standard distance is defined as the *quadratic mean of distance between each location and mean centre*:

$$S_{xy} = \sqrt{\sum_{j=1}^{L} \frac{(d_{jMC})}{L}} \tag{3.8}$$

where j refers to the work location and MC to the mean centre of the work locations. The mean centre is the mean of the x and y coordinates associated with the work locations.

- S_{xy} = the standard distance of work locations.
- Dj_{MC} = the distance between each work location j and MC.
- L = the total number of locations for a work activity.

The interpretation of S_{xy} is relatively straightforward: a larger standard distance indicates a wider dispersion of work locations on a given day.

3.3. Methodology

Bearing in mind that the aim of our analysis was to investigate the relationship between the fragmentation of work activity and ICT, we chose the following approach. First, following some descriptive analyses, we examined bivariate correlations concerning the association between the fragmentation measures and ICT. Next, we applied k-means clustering to identify a small number of classes (henceforth referred to as representative patterns) with internal similarities in fragmentation behaviour. The temporal and spatial fragmentation measures described in Table 1 were used as an input of the clustering algorithm. In the final stage, a multiple discriminant analysis (MDA) was applied for two purposes; (i) to investigate the differences among representative patterns in terms of ICT use, work, personal, and household attributes; (ii) to identify the variable that is the most important factor of the representative pattern of fragmentation. The representative pattern of fragmentation was used as a dependent variable in the MDA. In this study, ICT and work-related variables serve as explanatory (discriminant) variables together with personal/household variables.

4. Study findings

4.1. Preliminary analysis

In Table 2, temporal and spatial fragmentation is compared across ICT possession groups. The descriptive results in this table indicate in general that work activities appear to be more fragmented temporally and spatially for those individuals with a PDA, personal computer with internet connection, and laptop. This finding is consistent with studies by Couclelis (2003), Lenz and Nobis (2007) and Hubers et al. (2008a). With regard to the first dimension of fragmentation, we see clearly that those individuals with a PDA on average have more episodes at stationary and non-stationary locations than those without one. This difference is statistically significant. Furthermore, the results suggest that individuals with a laptop work at more different locations resulting in a more spatially as well as temporally fragmented work pattern than those without a laptop (p = 0.012). It appears that a PDA is especially important in temporal fragmentation, whereas a laptop seems to contribute more to spatial fragmentation. Regarding the second dimension of fragmentation, the results indicate that work episodes for those with a PDA are more disaggregated into different subtasks than those without a PDA. At the same time, the spatial distribution of work episodes shows that work activities for PDA owners is more evenly distributed across different locations than for non-owners. The result of the configuration of the fragments shows that there is statistically significant evidence that work episodes are dispersed more evenly across a day for those individuals with a PDA than for those without PDA. As expected, individuals with a personal computer or a laptop with internet connection tend to have a significantly more widely dispersed pattern of work locations.

Table 2
Comparison of fragmentation measures among ICT possession groups.

		Nobs	PDA		Sig level [t test]	PC with internet		Sig level [t test]	Laptop		Sig level [t test]
			With 85	Without 807		With 714	Without 178		With 235	Without 657	
Temporal fragmentation											
Number of fragments	E	Mean	15.5	11.7	p = 0.000	12.3	11.2	p = 0.183	12.7	11.8	p = 0.214
	E stat	Mean	14.3	11.2	p = 0.003	11.7	10.7	p = 0.731	11.9	11.4	p = 0.416
	E non-stat	Mean	1.16	0.48	p = 0.001	0.55	0.5	p = 0.077	0.81	0.41	p = 0.011
Distribution size of fragments	*T_index*	Mean	0.54	0.45	p = 0.000	0.47	0.43	p = 0.032	0.48	0.45	p = 0.169
Configuration size of fragments	T_{day} (h)	Mean	2.87	2.36	p = 0.017	2.40	2.39	p = 0.942	2.45	2.38	p = 0.662
Spatial fragmentation											
Number of fragments	L stat	Mean	1.88	1.9	p = 0.888	1.94	1.75	p = 0.077	2.04	1.85	p = 0.052
	L non-stat	Mean	0.66	0.3	p = 0.003	0.32	0.36	p = 0.589	0.44	0.29	p = 0.012
Distribution size of fragments	*S_index*	Mean	0.18	0.12	p = 0.007	0.12	0.12	p = 0.863	0.16	0.11	p = 0.002
Configuration size of fragments	S_{xy} (km)	Mean	4.1	3	p = 0.251	3.27	2.47	p = 0.002	4.81	2.5	p = 0.000

4.2. Representative patterns of fragmentation

Whether different patterns of fragmentation exist was tested using a *k*-means clustering algorithm. In order to determine the number of classes, preliminary analyses were conducted by examining the fragmentation behaviour patterns of 891 cases. In particular, two- to seven-class solutions were tested. This procedure revealed that a three-class partition led to the most essential and readily interpretable differences in fragmentation behaviour. In addition, when four or more classes are used, the sample size of the fourth and rest classes decreases enormously and the sample distribution becomes less equal. On the other hand, the capability of a two-class solution to represent all aspects of fragmentation behaviour is also limited. Finally, we therefore chose a three-class solution.

The descriptive statistics of the fragmentation measures of each pattern are presented in Table 3; the representative patterns can be seen to differ in terms of the temporal fragmentation of work

Table 3
Descriptive statistics of fragmentation measures of each pattern.

	Symbol	Representative patterns of fragmentation						Significant level [ANOVA]
		Pattern A (N = 237)		Pattern B (N = 440)		Pattern C (N = 215)		
		Mean	SD	Mean	SD	Mean	SD	
Temporal fragmentation								
Total number of episodes for work activity on the day	E	5.03	5.18	12.3	7.93	19.03	11.9	p = 0.000
Number of episodes at stationary location	E stat	4.65	4.65	11.9	7.62	18.3	10.8	p = 0.000
Number of episodes at non-stationary location	E nonstat	0.38	1.36	0.40	1.23	1.01	2.96	p = 0.000
Total time spent on work activity (min)	T	113.2	91.1	449.6	70.6	650.2	112.3	p = 0.000
Distribution of work episodes across subtasks	*T_index*	0.28	0.27	0.53	0.20	0.53	0.19	p = 0.000
Spread index of work episodes across day (h)	T_{day}	1.34	2.67	2.59	1.23	3.20	1.50	p = 0.000
Spatial fragmentation								
Total number of work locations	L	1.00	0.72	1.46	0.83	1.72	1.07	p = 0.000
Number of non-stationary work location on the day	L non-stat	0.06	0.24	0.04	0.20	0.13	0.34	p = 0.000
Distribution of work episodes across locations	*S_index*	0.12	0.22	0.11	0.20	0.15	0.22	p = 0.136
Spread index of work locations (km)	S_{xy}	1.46	4.84	2.70	6.85	5.76	12.68	p = 0.000
N = 892								

Table 4
ICT, work and personal-household characteristics of representative patterns.

29 Variables, 3 groups N = 884	Pattern A *Less spatially and temporally fragmented work pattern* N = 235		Pattern B *Less spatially and more temporally fragmented work pattern* N = 437		Pattern C *More Spatially and temporally fragmented work pattern* N = 212		Wilks' Lambda	F	Sig.
	Mean	Std. deviation	Mean	Std. deviation	Mean	Std. deviation			
ICT-related variables									
Non-work ICT duration [min]	42.7	59.0	32.9	47.0	25.5	41.8	0.984	6.17	0.002
Non-work communication [min]	28.4	27.7	24.1	26.7	22.9	28.8	0.994	2.38	0.093
Frequency of mobile phone calls: high [D]	0.12	0.33	0.14	0.35	0.26	0.44	0.979	8.46	0.000
Frequency of land line phone calls: high [D]	0.15	0.36	0.17	0.38	0.32	0.36	0.979	8.46	0.000
Possession of PDA [D]	0.08	0.27	0.12	0.32	0.10	0.31	0.997	1.00	0.369
Possession of laptop [D]	0.27	0.45	0.27	0.44	0.35	0.48	0.995	2.09	0.124
Possession of PC [D]	0.90	0.29	0.90	028	0.84	0.36	0.994	2.21	0.109
Does employer pay for internet at home? [D]	0.09	0.29	0.09	0.29	0.15	0.36	0.993	2.56	0.078
Combined phone/internet package [D]	0.52	0.50	0.55	0.50	0.58	0.49	0.998	0.83	0.434
Internet experience [years]	8.25	4.07	9.09	3.55	9.29	3.54	0.988	4.73	0.009
Work related variables									
Education: high [D]	0.75	0.44	0.79	0.41	0.90	0.31	0.981	7.58	0.001
Commute distance [km]	11.0	16.1	12.3	15.8	16.5	18.0	0.984	6.16	0.002
I work ...days at home per week [D]	0.41	0.49	0.39	0.49	0.53	0.50	0.999	0.56	0.572
Occupation: manager [D]	0.07	0.26	0.06	0.23	0.09	0.29	0.997	1.28	0.281
Occupation: high professional [D]	0.32	0.47	0.45	0.50	0.53	0.50	0.978	8.79	0.000
Occupation: low professional [D]	0.27	0.44	0.30	0.46	0.20	0.40	0.992	3.03	0.049
Occupation: clerical [D]	0.13	0.34	0.13	0.33	0.09	0.29	0.998	0.76	0.466
Occupation: service worker [D]	0.08	0.26	0.03	0.18	0.03	0.22	0.993	2.91	0.055
Occupation: skilled worker [D]	0.04	0.20	0.02	0.14	0.02	0.16	0.995	2.26	0.105
Personal and household attributes									
Male [D]	0.37	0.48	0.44	0.50	0.63	0.48	0.963	14.8	0.000
Age [years]	47.7	11.3	44.8	10.9	45.5	10.5	0.988	4.84	0.008
Household type: single [D]	0.25	0.44	0.23	0.42	0.19	0.40	0.997	1.03	0.359
Household type: partner and child [D]	0.28	0.45	0.33	0.47	0.31	0.46	0.998	0.63	0.531
Small children: [D]	0.26	0.44	0.29	0.45	0.25	0.43	0.999	0.52	0.597
Urbanization degree: less [D]	0.30	0.46	0.41	0.49	0.39	0.49	0.990	3.77	0.023
Household income: less [D]	0.24	0.43	0.25	0.43	0.15	0.35	0.989	4.25	0.015
Household income: high [D]	0.45	0.50	0.45	0.49	0.60	0.49	0.984	6.41	0.002
Number of cars per household	1.17	0.71	1.06	0.78	1.25	0.78	0.990	4.63	0.010
Working hour: partner	19.62	18.10	18.1	17.6	19.1	17.0	0.999	0.56	0.572

activity. The differences are statistically significant. We can distinguish between fragmentation patterns according to degree of fragmentation. The patterns can be characterized as follows:

- Pattern A: *a less temporally and spatially fragmented* work pattern (or concentrated).
- Pattern B: *a less spatially and more temporally fragmented* work pattern.
- Pattern C: *a more spatially and temporally fragmented* work pattern.

In pattern A individuals spent on average 113 min on paid work, while a small number of work episodes were concentrated in time. In pattern B, work activities consisted of 12.3 episodes on a given day; this large number of episodes was performed at stationary locations, taking on average 7.48 h. Work activities are fragmented into episodes of different subtasks that are characterized by a locally clustered pattern. Pattern C is characterized by the highest number of episodes per day with the longest work duration; work episodes appear to be dispersed more evenly across the day (that is, morning, afternoon, evening).

The representative patterns also differ in terms of spatial fragmentation. Based on mean indicator values for the measures of spatial fragmentation (Table 3), the differences are significant, except for the difference in *S_index* (*distribution of work episodes across different location*). Perhaps the work activities are mainly performed at a limited number of locations. The spatial fragmentation of representative patterns can be summarized as follows: work activities in pattern A are carried out at one fixed location. The spatial distribution of work episodes in this pattern is similar to that in pattern B. The work activities of pattern B are conducted at on average 1.46 locations, whereas the spatial distribution of work episodes is less. Pattern C is characterized by the highest number of stationary and non-stationary work locations. Work episodes appear to be dispersed spatially; the work locations tend to be evenly spread out. However, in Table 3 the high-level of within-pattern variation for some fragmentation measures is noteworthy; the standard deviation of the spread of work locations is particularly high for pattern C. This is probably owing to the fact that one-day data were used (see Hanson and Huff, 1986). Additionally, a high mean value is associated with a high standard deviation. For example, people who work long hours also have more variation in their working hours.

4.3. Estimation results of MDA

The multiple discriminant analysis is carried out with 29 discriminant variables to investigate the differences among representative patterns in terms of the independent variables and to test whether aspects such as ICT ownership and experience, work-related variables, and household characteristics are associated with particular representative patterns of work activity.

First, a series of One Way ANOVAs was performed on the analysis sample to test each independent variable's potential before the model was created. The general overview of the ICT, work, and personal and household-related attributes of the representative patterns are discussed below.

Table 4 suggests that, in terms of ICT-related variables, pattern A (*a less temporally and spatially fragmented work pattern*) is associated with the highest non-work ICT duration. Pattern C (*a more spatially and temporally fragmented work pattern*) is characterized by the highest frequency of mobile and landline phone calls and the longest Internet experience. These outcomes are in line with our earlier hypotheses that the use of and experience with ICT contributes to more fragmented work patterns. It should be noted, however, that the causality of this effect is unclear. It is likely that those whose work organization allows for fragmentation of the work activity will have used ICTs more in order to effectuate working from home and other places.

With respect to work-related variables, pattern C has the highest share of highly-educated professionals, whereas pattern A has the highest share of low level professionals. Pattern C also includes individuals with the longest commute distances. These figures suggest that more fragmented patterns are associated with highly-educated professional workers. Their organizations allow them to manage their work relatively independently, which allows them to work from places other than the office and outside office hours. This conclusion is consistent with Kakihara (2003). At the same time, these workers use fragmentation (for instance, working from home or in transit) as a means of working for more hours. The less fragmented patterns contain relatively more low level professional

Table 5
Discriminant function of fragmentation of work activity.

Function	Eigen-value	% Of variance	Canonical R	Wilks' Lambda	Chi-square	df	p-Level
a. Eigenvalues and Wilks' Lambda							
1	0.16	66.00	0.37	0.79	194.0	62	0.000
2	0.08	34.00	0.27	0.93	67.8	30	0.000
			Function 1				Function 2
b. Functions at group centroid							
Pattern A			−0.04				2.81
Pattern B			−0.48				−0.31
Pattern C			0.62				0.23
Discriminant variables			Standardized canonical discriminant function 1				2
c. Standardized canonical discriminant function coefficients							
ICT-related variables							
Non-work ICT duration [min]			−0.316				−0.007
Non-work communication [min]			−0.128				−0.132
Frequency of mobile phone calls: high [D]			0.184				−0.142
Frequency of land line phone calls: high [D]			0.376				−0.143
Possession of PDA [D]			−0.173				0.227
Possession of laptop [D]			−0.044				−0.169
Possession of PC [D]			−0.218				0.006
Does employer pay for internet at home? [D]			0.083				−0.076
Combined phone/internet package [D]			0.124				0.017
Internet experience [years]			−0.026				0.494
Work related variables							
Education: high [D]			0.281				−0.516
Commute distance [km]			0.161				−0.102
I work ...days at home per week [D]			−0.113				−0.185
Occupation: manager [D]			0.401				0.286
Occupation: high professional [D]			0.938				0.823
Occupation: low professional [D]			0.645				0.763
Occupation: clerical [D]			0.535				0.279
Occupation: service worker [D]			0.311				−0.070
Occupation: skilled worker [D]			0.131				−0.164
Personal and household attributes							
Male [D]			0.519				−0.091
Age			−0.275				−0.241
Household type: single [D]			−0.121				−0.301
Household type: partner and child [D]			0.055				0.206
Small children: [D]			−0.309				−0.041
Urbanization degree: less [D]			−0.022				0.101
Household income: less [D]			0.063				0.228
Household income: high [D]			0.068				−0.146
Working hour: partner			−0.076				−0.219
Number of cars per household			0.016				−0.114

workers; these people are less flexible in organizing their work activities in time and across space.

Table 4 shows that the representative patterns differ in terms of personal and household characteristics. People who belong to pattern A (*less temporally and spatially fragmented work pattern*) are most likely to be women, to be senior, who live in single-person households, or have a partner who has longer weekly working hours. The gender result seems to be consistent with findings of Hubers et al. (2008b) that women on average have fewer paid work episodes, and thereby have a less fragmented work pattern than men. It is presumably because women shoulder more familial responsibilities than men (Frusti et al., 2003).

Pattern B (*less spatially and more temporally fragmented work pattern*) consists of a greater fraction of people living in less urbanized areas, who live in a household with small children, and who have low household net incomes (Table 4). As expected, individuals in pattern C (*more spatially and temporally fragmented work pattern*) are more likely to be men, live in a household with a higher net income and a high number of cars. Similarly, people who live in a household with a higher net household income also tend to have more spatially- and temporally-fragmented work patterns. This is to be expected, because individuals with higher household incomes tend to have more purchasing power and can afford advanced ICT devices and services more easily than can individuals with lower household incomes. Another highly significant household-related variable is the number of cars per household. A large fraction of people in pattern C has a large number of cars per household, indicating that car availability increases the opportunity to have a more fragmented work pattern.

In addition to analysing the significance of each independent variable for fragmentation, we estimated discriminant functions that show the weights of the included variables. The MDA revealed that two discriminant functions were significant in distinguishing among the three patterns of fragmentation. The eigenvalues associated with each function were 0.16 and 0.08, respectively (Table 5a), indicating that the two functions together accounted for 24% of the variance in the discriminating variables. The group centroids are presented in Table 5b. We can see that Function 1 primary distinguishes pattern C and B from Pattern A and Function 2 discerns pattern A from the other patterns. The relative importance of each independent variable in predicting the dependent variable was assessed by the standardized canonical discriminant function coefficient (Table 5c). It indicates that the *occupation variables, education, internet experience* and *gender* are the most capable of discriminating among groups of fragmentation patterns.

5. Conclusion

Using data obtained from a two-day activity-travel-communication diary survey in the Utrecht–Amersfoort–Hilversum region in the Netherlands, we examined the fragmentation of work activities. The main aim has been to identify some distinct typical fragmentation pattern types and test whether ICT possession and usage, work-related, and sociodemographic factors are associated with these fragmentation patterns. The study has shown that there is heterogeneity in the fragmentation of work. Based on a simultaneous analysis of temporal and spatial fragmentation measures, we have identified three internally homogenous patterns of fragmentation that diverge in the degree of fragmentation.

The results of the multiple discriminant models show that the ICT variables and work together with personal-household attributes are associated with the fragmentation of work. However, the degree of association differs considerably among the representative patterns of fragmentation. Regarding the possession and usage of ICT, the highest frequency of mobile and landline phone calls and the longest Internet experience are associated with the more spatially and temporally fragmented work patterns, while the highest non-work ICT duration is associated with less fragmented work patterns. However, the causal relationship between ICT and the fragmentation of work activity is still unclear. More importantly, the study indicates that work, personal, and household-related variables are associated with fragmentation patterns more strongly than ICT variables are. Professionals and people with a high educational level, for instance, have a strong positive association with temporally and spatially fragmented work patterns. The occurrence of the fragmentation of paid work is also increasing for people with a long commute distance. With respect to the personal-household attributes, gender has a strong association with more fragmented work patterns, a result consistent with previous studies (Lenz and Nobis (2007), Hubers et al. (2008a,b)). This difference could be a consequence of the different working hours and household responsibilities of men and women. In addition to gender, age and the number of cars are positively associated with fragmentation of work.

In the current study, we have used cross-sectional data, so it is not known whether the fragmentation of paid work varies from day to day or how work activities are fragmented across weekdays and the weekend. The relationship between the fragmentation of work activity and non-work activity and the effect of the fragmentation of activities on travel demand are other important subjects. In the future, we will consider using a dataset for a longer period. The findings of this study offer new empirical evidence for the fragmentation of work activity and its association with ICT and non-ICT-related factors.

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