An organizational digital footprint for interruption management: a data-driven approach

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Abstract

Purpose – Interruptions are prevalent in knowledge work, and their negative consequences have driven research to find ways for interruption management. However, these means almost always leave the responsibility and burden of interruptions with individual knowledge workers. System-level approaches for interruption management, on the other hand, have the potential to reduce the burden on employees. This paper's objective is to pave way for system-level interruption management by showing that data about factual characteristics of work can be used to identify interrupting situations.

Design/methodology/approach – The authors provide a demonstration of using trace data from information and communications technology (ICT)-systems and machine learning to identify interrupting situations. They conduct a "simulation" of automated data collection by asking employees of two companies to provide information concerning situations and interruptions through weekly reports. They obtain information regarding four organizational elements: task, people, technology and structure, and employ classification trees to show that this data can be used to identify situations across which the level of interruptions differs.

Findings – The authors show that it is possible to identifying interrupting situations from trace data. During the eight-week observation period in Company A they identified seven and in Company B four different situations each having a different probability of occurrence of interruptions.

Originality/value – The authors extend employee-level interruption management to the system-level by using "task" as a bridging concept. Task is a core concept in both traditional interruption research and Leavitt's 1965 socio-technical model which allows us to connect other organizational elements (people, structure and technology) to interruptions.

Keywords Digital footprint, Trace data, Knowledge-intensive work, Classification tree, Interruptions, Management, Organizational situations, Features, Complexity, Data-driven

Paper type Research paper

1. Introduction

Employees in knowledge-intensive organizations face interruptions frequently. For example, they may lack detailed knowledge about what task to perform, how to carry out the task and with whom and/or using what kind of technology (Lyytinen and Newman, 2008). Such situations of uncertainty foster an individual to seek advice (Keith *et al.*, 2017) either in person or through information and communications technology (ICT) that leads to interruptions. Formally, an interruption occurs when the interruptee is working on a primary task and must suspend that task to attend to an interrupting task that was initiated by an interrupter (Trafton *et al.*, 2003). While interruptions as such have both negative and positive consequences (Addas and Pinsonneault, 2015, 2018; Sonnentag *et al.*, 2018), their unfavorable

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effects especially on performance and well-being (Baethge *et al.* (2015) (and references therein) has driven research to find out ways to manage interruptions.

In this study we focus on interruption management in the context of knowledge work. We define knowledge work as requiring extensive formal education and continuous on-the-job learning, transferable skills, low level of standardization, involving working with abstract knowledge and symbols and ranging from professional bureaucracies to self-managing teams where knowledge is as a primary production factor (Pyöriä, 2005). Typical examples would be engineers, legal, medical, or creative professionals, consultants, or journalists. A trend in recent decades has been to increase the autonomy of knowledge workers. For example, self-organized work, high levels of discretion and a high degree of task and working time flexibility are fairly common (Boxall and Winterton, 2018). In particular, interruption management is typically the responsibility of individual employees.

Indeed, also literature mostly highlights employee-level means for interruption management. The aim of these usually is to help knowledge workers mutually coordinate their actions so that interruptions become less frequent or to mitigate their adverse effects. First, there are strategies and technologies that address immediate reasons for interruptions (e.g. notification alerts of incoming messages, phone calls, etc.) from the point of view of the individual being interrupted (Mark *et al.*, 2012; Sykes, 2011). A second vein of interruption management literature aims to fit the needs of the interrupting party to those of the interrupted parties (Avrahami *et al.*, 2007), again often using various technical solutions (Dabbish *et al.*, 2007). However, in both cases interruption management primarily rests with individual knowledge workers, and interruptions are in a sense accepted as a ubiquitous issue of working life (Puranik *et al.*, 2020).

In this paper we challenge this view and argue that also the management should take responsibility of interruption management. We propose that knowledge is needed about the system where work is performed and from where interruptions emerge. Crucially, this system is something that also the management can influence. The main contribution we make is a methodology for system-level interruption management. To this end we propose a data-driven approach for identifying what we call "interrupting situations." As the main theoretical framework we take Leavitt's (1965) model of socio-technical systems that is composed of four elements: task, people, technology and structure. We use Leavitt's elements to identify interrupting situations because "task" is a core concept in both traditional interruption research and Leavitt's socio-technical model and serves in our model as a bridge between employee- and system-level interruption management.

We also argue that by considering the system-level, management can employ a wider set of means to interruption management than what is available to individual knowledge workers. In particular, the four elements in Leavitt's model are interconnected, and when one element of the system is subject to a change, the other elements may have a balancing role. This balance can be retained along a variety of paths (Lyytinen and Newman, 2008). For example, if more tasks emerge than were planned, employees may be forced to switch from their ongoing task to another through interruption to carry out the increased workload. This way the system will remain in balance, but this happens potentially at the cost of the employees' well-being (Chen and Karahanna, 2018). However, if it is possible to identify situations associated with interruptions at the system-level, management can take action on the other situational elements to regain balance. In this way, the burden on employees to maintain balance through interruptions can be eased.

Table 1 shows examples where we utilize Leavitt's elements to describe situations from where interruptions may emerge. The examples are based on our experience of collaborating with knowledge-intensive organizations. The interrupting situations are described in the left column. The column on the right has proposals for system-level interruption management, where the structural element of Leavitt's model often takes a balancing role. Note that the situations described in the left column in no way prevent the organization from functioning, but they do increase the knowledge workers' need to deal with interruptions. This example demonstrates how in addition to individual-level means to tackle effects of interruptions, interruption management can also be carried out at a system-level by avoiding the emergence of interrupting situations.

However, this requires practical means for management to identify those socio-technical situations that relate to high levels of interruptions. Identifying these would constitute the first step of interruption management at the system-level. *Hence, the objective of the study we present in this paper is to demonstrate an approach for identifying socio-technical situations where interruptions occur most/least probably.*

This is a challenging task because as an organization undergoes change, also the interrupting situations within the organization evolve over time. To identify these situations, a nearly real-time view to the activities in an organization is required. We argue that this can be provided by data from various ICT systems used by knowledge workers. As the usage of ICT becomes more prevalent, increasing amounts of such *trace data* (Crowston, 2017) are being collected and stored. In the context of interruption management, automatic data acquisition combined with suitable analytics would provide management with timely information about interrupting situations and their temporal change.

As a practical tool for identifying interrupting situations from trace data, we use the classical machine learning method of classification trees (Breiman *et al.*, 1984). Importantly, when using classification trees the associations between elements in a situation are not needed to be known in advance. Rather, the method identifies the combination of elements best associated with the level of interruptions from the data. This is crucial, as it is in general difficult to define in advance what constitutes an interrupting situation as the organization evolves. Classification trees also have the benefit of being able to capture nonlinear dependencies between independent variables, while still allowing easy interpretation of the model that is required to identify the interrupting situations in practice.

However, automatic acquisition of trace data is in practice rather nontrivial. Organizational data almost always reside across a variety of systems that in general do not provide convenient means for centralized analytics as required by our approach.

Table 1. Examples of interrupting situations and their system-level management

Examples of interrupting situations	Examples of system-level interruption management, the structural element having a balancing role
• *Tasks increase* in an unplanned manner due to a sudden change in the customers' needs • *New attributes are added to the tasks*, the implementation of which is not clear	• Introduce a *centralized customer service* for unexpected tasks to reduce the amount of employees who are affected by the changes • Systematically plan for *slack in schedules* to increase resilience toward sudden increases in workload
• *New guidelines* are introduced, but relevant documentation has not been updated to reflect the changes • *Colleagues change* due to new work arrangements; the new people are not familiar with all details • *More meetings* are scheduled to familiarize the new employees with the ongoing tasks	• Organize *training* about the new guidelines to prevent the need for employees to pass knowledge among themselves • *Postpone reorganizing* to prevent employees from having too many new coworkers to reduce the need for orientation sessions
• The number of *ICT systems doubles* after merging two units that were using separate systems	• *Migrate data* from System B to System A and *Sunset System B* to prevent the need for running two systems in parallel

Therefore, rather than collecting data from systems, as this is technically challenging, we conduct a "simulation" of automated data collection by asking employees of two companies to provide similar information concerning situations and interruptions through weekly reports. Then, we use classification trees to show that this data can be used to identify situations across which the level of interruptions differs. As our objective is to show that trace data may have practical management applications, the results of the study mainly serve the purpose of exemplifying the potential of the approach. For a real use case we advocate the use of real trace data rather than repeated questionnaires.

The paper is structured as follows. First, we present related work on traditional employee-level interruption management. Second, we develop a data-driven approach for system-level interruption management based on system-level data. Third, with a simulation-like empirical study, we demonstrate that identifying interrupting situations is possible with our approach. Finally, we conclude the paper with three observations. The first is theoretical, where we discuss how a socio-technical approach goes beyond employee-level interruption management and enables to consider other existing system models, which may be helpful also in the context of interruption management. Second, we discuss insights for management practice using the model of system-level handling of interrupting situations. The third observation is methodological, where we argue that the developed data-driven methodology may be useful in general, and not only in the context of interruption management. This methodology also includes challenges with a digital footprint, to which we propose solutions.

2. Background on interruption management

2.1 Effects of interruptions

Interruptions are frequently, daily if not on an hourly basis, faced by workers in knowledge-intensive organizations. Some of these interruptions can have positive outcomes. For example, when the interrupter needs something from the interruptee, and if this need is satisfied after the interruption, the interruption had a positive effect for the interrupter. Further, if the interruptee also receives useful information when communicating with the interrupter, the situation is positive for both parties (Addas and Pinsonneault, 2015; Dabbish and Kraut, 2004; Dabbish *et al.*, 2007; Avrahami *et al.*, 2007). Moreover, when the interruption does not require the interruptee to switch their attention from one context to another, there are no substantial negative consequences to task performance (Frese and Zapf, 1994). Recent studies have also found that interruptions can have an indirect positive effect on task performance. When the interrupted respond quickly to online messages, it led to a feeling of responsiveness and positive effect (Sonnentag *et al.*, 2018), or interruption may enhance task closure via which positive effects occur on work performance (Chen and Karahanna, 2018). Further, interrupted individual's interaction with the interrupter can simultaneously fulfill one's need for belongingness (Puranik *et al.*, 2021).

In spite of this, interruptions are mainly not intended to occur due to their adverse effects on cognitive processing (González and Mark, 2004; Addas and Pinsonneault, 2015). Immediate negative consequences of interruptions are the delay required to resume the primary task, an increased likelihood of making errors, decline of performance (Trafton *et al.*, 2003; Monk *et al.*, 2008; Speier *et al.*, 2003; Mark *et al.*, 2005; Addas and Pinsonneault, 2015) and stress (Galluch *et al.*, 2015; Mark *et al.*, 2008; Baethge and Rigotti, 2013; Puranik *et al.*, 2021). A recent study by Chen and Karahanna (2018) shows that work-related interruptions increase notably work exhaustion and slightly impede performance. A long-term consequence of interruptions is development of strain (Baethge *et al.*, 2015). Work-related stress has been shown to cause financial costs and loss of productivity (Hassard *et al.*, 2018). These negative consequences to performance and well-being have driven efforts to find means to manage and control interruptions.

2.2 Employee-level interruption management

Next, we review relevant aspects of the existing literature on interruption management. A typical immediate reason for an interruption in knowledge work is face-to-face communication (Sykes, 2011), email (Mark *et al.*, 2012; Kushlev and Dunn, 2015; Dabbish and Kraut, 2006; Addas and Pinsonneault, 2015; Galluch *et al.*, 2015) or instant messaging alerts (Mansi and Levy, 2013; Gupta *et al.*, 2013). The aim of employee-level interruption management has been to minimize disruptions associated with interruptions from the individual interruptee's point of view. Controlling the use of email has been an important focus of earlier work on ICT-mediated interruptions. However, while interruptions and stress have been shown to decrease during email-free periods (Mark *et al.*, 2012; Kushlev and Dunn, 2015; Sykes, 2011), the problem of overload still remains over longer time periods (Barley *et al.*, 2011; Dabbish and Kraut, 2006). Moreover, completely disconnecting from email and other communication systems may not be possible in many situations due to e.g. customer demands (Mazmanian, 2012; Mazmanian and Erickson, 2014).

The role of interrupter as the *initiator* of the interruption has led to other approaches to interruption management. In these the focus is on protecting the interruptee from interruptions by facilitating ways for the interrupter to initiate contact without disturbing excessively, for example, by timing interruptions at periods of low workload of the interruptee. Such approaches can be particularly successful when collaborators share team membership (Dabbish and Kraut, 2004). Examples of this are *common practices* for face-to-face communication (Sykes, 2011) or *quiet hours* during which others should not be approached. Of course, these may not work in all situations as the need to interrupt is unforeseen and impossible to plan for in advance (Perlow, 1999).

Recent interruption management approaches consider *collaborative scenarios* where the needs of the interrupter must be recognized as well. McFarlane (2002) has argued that cooperation can be harmed if only the interruptee has control over when contacting can take place, and in a similar vein Avrahami *et al.* (2007) point out that urgency of the task the interrupter is performing must also be considered. From the interruptee's point of view, the more detailed information one has about the interrupter's task, the easier it is to align one's own behavior to the interrupter's goals (Dabbish *et al.*, 2007). An important technical means to facilitate collaborative interruption management are awareness displays that aim to enhance communication between the interrupter and interruptee. Research on awareness displays is abundant and can be situated in various contexts, such as safety-critical systems, distributed teamwork and knowledge work (Tang, 2007; Birnholtz *et al.*, 2011; Palacio *et al.*, 2012; Peters *et al.*, 2017).

In conclusion, common to most existing scholarly work on interruption management is that the final responsibility of initiating an interruption, or avoiding being interrupted by others, remains mostly with individual employees. However, employees may in the end have only limited control over their tasks. To the best of our knowledge, there is no literature on efforts to avoid interruptions by providing management with methods to reduce occurrences of interrupting situations.

3. Data-driven approach for system-level interruption management

In this section we describe our approach to identify interrupting situations. We first establish a link from employee-level interruption management to socio-technical system-level interruption management. After this, we discuss how complex organizations warrant a data-driven methodology to identify evolving relationships between socio-technical elements that are associated with interrupting and non-interrupting situations. Therefore, an important ingredient of our approach is the digital footprint left in work-related ICT systems by employees as they carry out their tasks. We then describe simple numerical features that can be obtained from this type of data and argue how they fit within Leavitt's (1965) model. We define socio-technical situations in terms of these features and propose to use a supervised machine learning method (classification trees) to identify interrupting vs non-interrupting situations in a data-driven manner. In the study discussed in the next section we demonstrate this approach by asking employees to report these features through a diary-like questionnaire.

3.1 Task as a part of interruptions and socio-technical systems

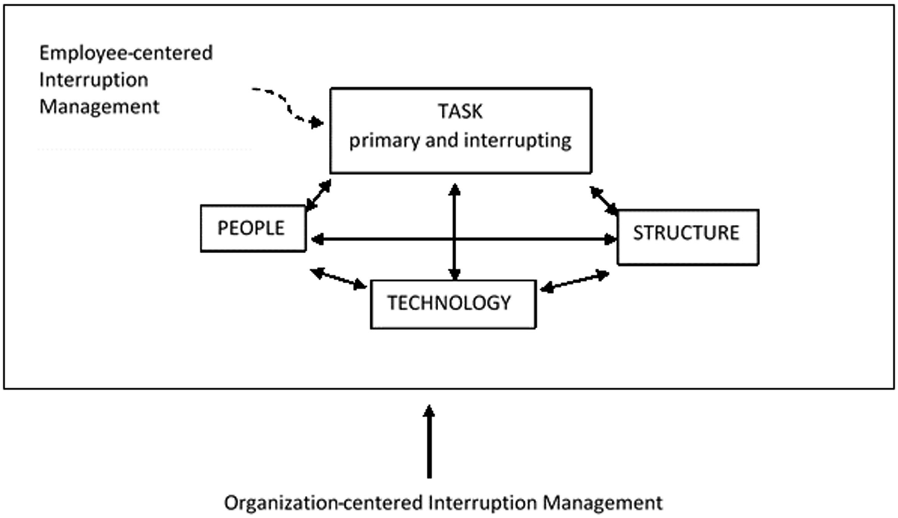
Primary task and interrupting task are central notions in the classical interruption management literature as reviewed above. Employees direct their tasks, possibly with the help of technology, to not be interrupted by others, as well as to not be the interrupter themselves. However, we argue that interrupting tasks often arise from unforeseen changes within a socio-technical system. A classical model of the system is Leavitt's (1965) diamond. This represents a framework that is often employed within socio-technical research and that demonstrates how the four organizational elements (task, people, technology and structure) are all central and interconnected. We use them to identify interrupting situations.

First, note that "task" is a central concept both in Leavitt's model, as well as the interruption management literature. In particular, Leavitt considers tasks as "the production of goods and services," i.e. the fundamental activities in an organization. We make the case that both primary tasks, as well as interrupting tasks can be understood as "meaningful subtasks" as defined by Leavitt. Next, at the core of Leavitt's model is the assumption that a change in any of the four elements may result in changes to the other three. Furthermore, "these changes could presumably be consciously intended, or they could occur as unforeseen and often costly outcomes of efforts to change only one or two of the variables" (Leavitt, 1965, p. 1145). It is this unforeseen change that we argue is underlying many interruptions. In a recent review Puranik *et al.* (2020) included an unforeseen element in the definition of interruption: "A work interruption is an *unexpected* suspension of the behavioral performance of, and/or attentional focus from, an ongoing work task" (p. 817).

Figure 1 summarizes how we extend employee-level interruption management to organizational interruption management via Leavitt's model. Here the employee-level approaches are understood to focus mainly on the task element that encompasses both the primary as well as the interrupting task. System-level interruption management, on the other hand, takes a holistic approach and jointly considers all four elements. But for this relationship between interruptions and Leavitt's elements to result in a practical interruption management approach, we need a methodology to identify what combinations of elements relate to interruptions.

Next, we discuss our assumptions about the relationship between the four elements and interrupting situations. First, organizations can be described in terms of complex adaptive systems (Dooley, 1997; Schneider and Somers, 2006) as also Leavitt (1965) already proposed. This implies for example that phenomena at work are emergent, i.e. they arise from unplanned interactions of micro-level components (Goldstein, 1999). In complex adaptive systems, the relationships between parts that constitute the system (in our case the Leavitt's elements) and system output are dynamic, nonlinear, discontinuous and uncertain (Cox *et al.*, 2007). Hence, we argue that the precise interdependencies among Leavitt's elements may vary between situations and between organizations, and we only assume that the elements jointly contribute to different situations in which interrupting tasks arise. Importantly, these situations evolve over time as an organization continuously adapts to its operating environment.

Second, we understand complexity as *continuous change* that appears for the employees as *varying situations* that cannot be very accurately planned for in advance. The employees must nonetheless accomplish their work in these varying situations, in which it may not be certain what task to perform, how to carry out the task and with whom and/or by what kind of



Source(s): Leavitt's (1965) sociotechnical model is combined with the traditional interruption model (Trafton *et al*., 2003) via the bridging element "task"

Figure 1. Employee- and system-level interruption management

technology (Lyytinen and Newman, 2008). The uncertainty inherent to these situations fosters an individual to seek advice (Keith *et al.*, 2017). Advice seeking usually takes place through ICT or in person, resulting in one individual possibly interrupting another.

Above we argued that the situations evolve over time. This presents a challenge that cannot be tackled by a static model. To properly consider the evolving nature in relations between elements, we utilize a configuration approach. The configuration theory describes organizations as bundles of interdependent parts that should be studied in a holistic manner (Meyer *et al.*, 1993). In this study we apply the configuration model, in which relations between elements are not defined in advance (Sinha and Van de Ven, 2005). This model only assumes that the elements *jointly* characterize different situations in which interrupting tasks may or may not arise. To this end we propose to employ a data-driven approach that from empirical data of situational features, representing Leavitt's elements, identifies socio-technical situations associated with different levels of interruptions. For this we need an approach that can model complex, nonlinear phenomena and is free of assumptions about relationships between elements. A classical machine learning technique that satisfies these requirements are *classification trees* (Breiman *et al.*, 1984). Later, after defining interrupting situations more formally, we describe how these can be found with classification trees in a data-driven manner.

3.2 Features of socio-technical situations

Choosing informative features is a crucial step in data-driven analytics and other machine learning applications. In this section we discuss the four elements of Leavitt's (1965) model to describe features that we define organizational situations with. In the following we call these *situational features*. Since our goal is to identify interrupting from non-interrupting situations, the situational features should ideally have some known relevance for interruption management. Moreover, situational features should be easily computed from trace data collected in company-wide ICT systems (Crowston, 2017). The latter of these requirements also means that the features will be "factual," rather than abstract dimensions as commonly encountered in, e.g. survey instruments. To meet these requirements, we propose to use as situational features the *quantities* of events, people and other simple things an employee encounters at the workplace in some fixed time period. The features we define are not intended to constitute an exhaustive list. Rather, they form a small set of reasonable factual aspects of knowledge work that cover all four change elements and can be potentially computed from trace data (Crowston, 2017), if available. Also, since in the study we must rely on manual data collection in the form of a diary-like questionnaire, the number of situational features cannot be very large to keep the questionnaire short enough. (If the features were collected from trace data, nothing would prevent us from using even hundreds of features.) The situational features we have chosen are summarized in Table 2.

3.2.1 Task. *Task* describes the work systems goals, the way the work gets done and the way in which an organization orients toward and adapts to its environment and meets the requirements and constraints of its different stakeholders (Lyytinen and Newman, 2008).

A crucial property of tasks in relation to interruption management is that they can be subject to unforeseen changes (Leavitt, 1965), and thereby introduce uncertainty to work performance. Task uncertainty has been studied especially in the context of IT projects, in which it is defined as the level of technological novelty and project complexity as follows: "Higher task uncertainty implies high variability in and unpredictability of exact means to accomplish the task, in turn leading to poorer task outcomes" (Tatikonda and Rosenthal, 2000, p. 75). When not knowing how to proceed, task uncertainty drives advice-seeking behavior (Keith *et al.*, 2017). In advice-seeking behavior, the advice seeker requests advice regarding a particular intellectual task in order to achieve a desired outcome (Stokman and Doreian, 1997). Consequently, we argue that task uncertainty and related advice-seeking behavior leads to interrupting tasks. Additionally, a positive association between interruptions and the number of tasks, defined as routine work activities per hour was observed by Kirmeyer (1988). The situational feature we propose to represent the change element "task" with is the *number of tasks* an employee carries out in some fixed time period.

Availability from trace data: Depending on the type of knowledge work, the number of tasks may be available from a system specific to the work in question. For example, in the context of software engineering, source code version control systems (e.g. Git and Mercurial) or issue trackers (e.g. Jira) can provide data from which the number of tasks of an individual

Table 2.
Organizational change elements and corresponding situational features

Organizational change elements	Situational feature(s)	Availability from ICT systems
Task	- The number of tasks	- Context dependent - E.g. version control systems and issue trackers (for software engineers) - E.g. CRM systems (for account managers)
People	- The number of collaborators (colleagues and customers, etc.) - The number of team memberships	- Email/Calendar/Instant messaging - Working time reporting systems
Technology	- The number of ICT systems - Problems with ICT systems	- IT-support issue tracking systems - For cloud-based applications: network monitoring
Structure	- The number of projects - The number of guidelines - The number of meetings - The number of locations	- Resource planning systems - Customer billing systems - Email/Calendar - Physical access control systems

employee can be inferred. Or, as another example, for account/sales managers, relevant information may be available from customer relationship management (CRM) systems (e.g. Salesforce). Finally, especially in the context of higher education, the number of tasks could be obtained from usage logs of online learning environments (e.g. Moodle).

3.2.2 People. People include an organization's members and its main stakeholders who collaborate and carry out the work as managers, employees, customers or any individual or group that can set up a requirement toward the organization (Lyytinen and Newman, 2008).

Collaboration can take place either face-to-face or via ICT systems. In studies of constant connectivity, interruptions are viewed as something positive because of an increase in the experience of autonomy (Wajcman and Rose, 2011), but negative consequences of high levels of connectivity have also been proposed (Kolb *et al.*, 2012). In addition, a knowledge worker may be assigned to a number of different teams. O'Leary *et al.* (2011) argue that when working in, or with many different teams with different contexts, a knowledge worker has to switch between contexts often. Such multiple team membership may thus increase the number of interruptions. The situational features we propose to represent the change element "people" with are the *number of coworkers*, *number of customers/external collaborators* and *number of team memberships* an employee has within a fixed time period.

Availability from trace data: These situational features can be extracted from various communications systems. An email server (such as Microsoft Exchange) stores the emails and calendar entries of all employees, as well as keeps logs about system use. It does not directly store or make use of the number of collaborators an individual has been in contact with (either by email or by attending a common meeting), but an approximation of the number of colleagues as well as different team memberships is relatively easily obtained from email/instant-messaging/calendar data. The number of customers, on the other hand, can be inferred from systems used to report working hours for customer billing purposes, possibly after combining the data with those from a resource planning system.

3.2.3 Technology. Technology denotes tools such as problem-solving inventions like software and hardware technology and information systems. It includes all elements of the organization's technological core covering production, distribution and R&D technologies (Lyytinen and Newman, 2008). By ICT systems we refer to various software applications (e.g. productivity and reporting tools), cloud services, mobile applications, etc. that a knowledge worker uses to carry out work tasks and to communicate with others. ICT systems may suffer from weaknesses in design, compatibility and usability, along with the delays associated with software upgrades (Karr-Wisniewski and Lu, 2010). Therefore, when a knowledge worker uses different ICT systems, e.g. unforeseen incompatibility problems can cause interruptions. Additionally, an ICT system may function slowly or be unavailable due to software crashes, hardware failures or poor network performance (Karr-Wisniewski and Lu, 2010; Addas and Pinsonneault, 2015), meaning that problems with ICT systems may lead to interruptions as well. We propose to represent the change element "technology" with situational features' *number of ICT systems* and the *number of problems with ICT systems* an employee encounters within a fixed time period.

Availability from trace data: The number of different ICT systems and/or software used by an individual employee is less trivial to obtain from trace data. This information might be known from other sources, e.g. from information about software licenses. However, tools used in knowledge work are increasingly cloud based and accessed via a web browser. Counting the number of these is in principle possible by monitoring browser activity for different Uniform Resource Locator (URL) patterns that are associated with cloud services. The number of problems with ICT systems, on the other hand, may be possible to extract from application-specific error logs, as well as issue tracking systems of IT-support services.

3.2.4 Structure. Structure covers systems of communication, authority, workflow and work organizations as project-based management. It includes both the normative and behavioral dimension of activity (Lyytinen and Newman, 2008). We discuss "structure" in terms of projects, guidelines, meetings and locations.

Projects are a very common way to organize work (Sydow *et al.*, 2004). A recent study among software developers has found a strong correlation between the number of projects and the number of interruptions reported (Tregubov *et al.*, 2017). We argue that in the same vein as tasks, also projects are associated with interruptions via uncertainty. Sources of project uncertainty include lack of information, ambiguity, characteristics of project parties, trade-off between trust and control mechanisms and varying agendas in different stages of the project life cycle (Atkinson *et al.*, 2006). Also, a recent review concerning uncertainty has highlighted two main dimensions associated with uncertainty: missing information and interdependencies (Padalkar and Gopinath, 2016). We argue that when dealing with uncertainty at project level, interruptions may arise as a consequence of new information about priorities of various tasks and their evolving interdependencies.

We also consider that advice-seeking behavior applies to written guidelines and other documentation as well. That is, in addition to asking colleagues for advice, a knowledge worker seeks advice from various structured sources, such as websites, an organization's intranet, manuals, etc. The success of using community-based question-and-answer sites depends mainly on the will of their members to answer others' questions, so it is not evident that an advice seeker gets an answer (Calefato *et al.*, 2018), and an interrupting situation may emerge.

We define locational work as such where the employees "move a lot spatially, utilize different locations for work and communicate with others via electronic tools" (Koroma *et al.*, 2014, p. 120). A knowledge worker may move between primary workplace, customer's office or home. When moving from one location to another, employees may not be familiar with new locations and the possibilities they offer to accomplish work tasks (Mark and Su, 2010). For instance, there may be unexpected changes in situations, spaces and ICT in customer's office. Thus, we may argue that uncertainty within different locations creates a condition where interrupting tasks arise.

Finally, meetings are a fourth aspect of "structure." We consider both face-to-face meetings, as well as meetings mediated by ICT systems. In earlier work, meetings have been defined as a particular kind of interruption (Rogelberg *et al.*, 2006). Even when they are preplanned, meetings can interrupt the flow of work at an unsuitable time (Geimer *et al.*, 2015).

The situational features of "structure" are thus the *number of projects* an employee is working on, *number of guidelines* an employee consults, *number of meetings* an employee attends and *number of locations* an employee visits, all of these within a fixed time period.

Availability from trace data: The number of projects is available from resource planning systems, or customer billing systems. The number of meetings is easily obtained from email/instant-messaging/calendar data. Telework or work carried out in multiple locations is in simple situations reflected in logs of (physical) access control systems. If the locations an employee is working at do not fall under the same administrative domain (e.g. part of the work is carried out at the employer's offices, while part at customers' offices), similar information can be obtained from resource planning systems that show what customers or projects an employee is assigned to. Guidelines are less trivially obtained from trace data. However, depending on the type of knowledge work, the guidelines are often accessed online, and again it may be possible to count how many times an employee visits, e.g. certain websites (for example Stack Overflow in the case of software engineering).

3.3 Situation definition

Now that we have defined a number of situational features, we can define the situation itself. A *situation* is characterized in terms of *one or several situational features*. The situational features represent measurable information about the change elements within some fixed time period, as discussed above (Table 2). Formally a situation is defined by *a collection of situational features*. For example, some situation may be defined as having "few tasks AND plenty of meetings," while another situation may involve "very few projects AND plenty of customer work AND not so much telework." The situations we seek to identify each encompass the situation of several employees. For example, the situation with "few tasks AND plenty of meetings" encompasses all employees whose situation contains "few tasks" and "plenty of meetings" irrespective of the values taken by other situational features for those employees.

Moreover, as the situational features change over time, the organizational situations are *time evolving*. For some employee, a situational feature may occur in one time period with some quantity (e.g. there can be a lot of meetings during Week 1) and in another time period with another quantity (there are only a few meetings in Week 2). Therefore, not only can two employees reside in different situations in a given time period, but an individual employee can reside in different situations in two (consecutive) time periods. To take this temporal evolution into account, each situational feature must be measured over a number of consecutive time periods.

Finally, we address the question of the *length* of the time period in which the situational features are measured. The length of this time period is an important parameter, and for consistency it should be the same for all situational features. This can pose a problem if some features exhibit slower variation than others. For example, the "number of projects" an employee is engaged in may remain fairly constant over several weeks, possibly even months, while the "number of meetings" an employee attends can vary from one day to the next. It is thus important to strike a balance in setting the length of the time period so that it can capture both slowly, as well as quickly evolving situational features. In our study, we decided to use a time period of one week.

3.4 Interruptions in socio-technical systems

In this section we summarize our understanding of interruptions in socio-technical systems. Interruptions' immediate antecedents are well known as messages through different ICTs and face-to-face interaction, where interruptions are unexpected (Puranik *et al.*, 2020). We assume that these immediate antecedents are governed by a socio-technical system comprising tasks, people, technology and structure that frames the changing situations in which work is performed.

3.4.1 Interrupting and non-interrupting situations. Although interruptions are common, not all tasks are interrupted all the time. There exist situations where, e.g. uncertainty is low, and work progresses as planned. Hence, there is low to moderate novelty in tasks and coworkers, customers are familiar and guidelines are easy to find when needed. There is not much new to learn in the technology, and there are no substantial problems with its use. Hence, there is not so much need to seek advice.

We consider interruptions to emerge from socio-technical situations in an unplanned manner. No one plans interruptions in advance, neither the interrupter, the recipient of the interruption nor other actors (e.g. management) in an organization. Instead, the socio-technical elements (task, people, technology and structure) and their connections to interruptions can be the objects of system-level planning. To identify these situations, we use a lightweight data-driven approach.

3.4.2 Lightweight data-driven approach for situation identification. The approach we propose involves both ongoing data generation and analysis. The data are generated as described in Section 3.2 above and is accumulated in ICT systems as part the normal activities of an organization. The analysis takes place without prior hypotheses because the situations formed by the elements and their connection to interruptions have not been previously identified. Thus, the analysis is in general done by searching for structure in the data (pattern recognition) using data science tools and is not testing any specific structure using prior hypotheses. In this work we used the machine learning method of classification trees for carrying out the analysis.

A similar data-driven approach has been applied in interruptibility studies (Turner *et al.*, 2015; Choy *et al.*, 2016; Sarker *et al.*, 2020), in the field of human–computer interaction, using real trace data. For example, Anderson *et al.* (2021) provide new insights for the design of future interruption management systems for employee-level interruption management. They conducted an in-the-wild study with 16 participants for five weeks to collect data concerning individuals' application usage and survey to get information for roles and preference to be interrupted. As device-based features, they used for among other things the number of unique applications, number of unique activities, number of notifications and number of different application genres. They applied seven different data-driven models to predict individuals' interruptibility preferences. A classification tree is one of such models. The data and methodology are similar between our study and in the above mentioned interruptibility studies, but we consider the system level rather than that of individual employees.

3.5 Identifying situations from data

Now we move on to discuss how to identify interrupting and non-interrupting situations. To do this, we need data that contain both measurements of the situational features for the employees, as well as some information about the level of interruptions as perceived by the employees. The *level of interruptions* can be thought of as yet another situational feature, and we aim to *predict* this given the other features. That is, given a situation as expressed by a number of situational features, the model should give us an estimate of the average level of interruptions in that particular situation. This is a simple machine learning problem that can be solved with different techniques. But to *identify* situations, we need a method that allows us to describe the situations in terms of the situational features. This requirement rules out, e.g. neural networks or other "black box" models.

We chose *classification trees* (Breiman *et al.*, 1984) because of their lack of assumptions about associations between features (we take a configuration approach), their ability to uncover nonlinear dependencies (we assume the underlying phenomenon to be complex) and their structure that is easily turned into textual descriptions of situations in the form of simple *rules* (we need an interpretable model). *Each of these rules corresponds to a situation and the entire classification tree contains a number of different situations.* For example, a situation found by the algorithm might specify that "number of meetings $\leq$ 8 AND number of tasks $\leq$ 10." This rule captures all employees who in at least one time period had at most eight meetings and at most ten tasks. To each rule is also associated an estimate of the perceived level of interruptions in the situation expressed by the rule.

We also emphasize that the resulting situations, if any, are *found* by the classification tree algorithm; they are not specified in advance. This also concerns the *split points* in each condition (Numbers 8 and 10 in the example above). The algorithm evaluates a vast number of possible situations and returns those that provide the best explanations of variation in perceived levels of interruption. The objective of this analysis is thus not to test the fit of predefined situations but to *find the most descriptive situations in a data-driven manner.* Importantly, if none of the situations is strongly enough associated with a high or low level of interruptions, the algorithm *does not identify any situations*. In this case the resulting classification tree is empty. This would mean that in terms of the chosen situational features, no interrupting or non-interrupting situations can be identified.

4. Empirical study

Next, we present an empirical study that illustrates the approach discussed above in a real interruption management setting. Our basic objective is to show that interrupting vs non-interrupting situations can be identified by the approach described above. Simply put, a positive result is if for both organizations a non-empty classification tree is found, while an empty classification tree would constitute a negative result.

Under ideal circumstances the situational features are obtained from trace data collected in different organization-wide ICT systems. However, as discussed above, the data we would require are almost always dispersed across a multitude of heterogeneous systems. This makes their use for analytics nontrivial, and would require engineering efforts. However, as a preliminary demonstration of our ideas, we avoid these issues by replacing automated data acquisition with a simple, diary-like, web-based weekly questionnaire that aims to collect the same type of information available from ICT systems. This has the upside that we can "simulate" our data-driven approach with a fairly lightweight experiment, the main bottleneck of which is that participants must be willing to answer the same questions for eight consecutive weeks.

The situational features that we consider are those discussed above. We chose to measure each feature within consecutive time periods of one week. First, weekly quantities are reasonable when considering the rate of variation in the situational features that we chose to use. In the case of interruptions, a time period length of one day, or even one hour, would be ideal, but given our data collection method this is infeasible, and thus interruptions are also assessed at week level. Second, as we are collecting data by a self-reported questionnaire; we considered periods of one week to yield data of fine enough granularity for all variables of interest, without placing too heavy a burden on the respondents so that they would still be willing to take part in the study.

4.1 Participants

Two organizations engaged in knowledge work, Company A and Company B below, participated in the study. The companies were chosen by a form of convenience sampling. The authors had existing contacts to Companies A and B from an unrelated professional context, and when asked to take part in the study, both companies agreed. No other companies were contacted. Companies A and B were considered as suitable for the study because they represent areas of knowledge work in which interruptions are particularly prevalent (Company A: software engineering and Company B: back-office services). Also, the leading representatives of HR in both companies were familiar with problems caused by frequent interruptions, and thus had an interest in new solutions to manage interruptions. The recruitment of participants was done by contacting the HR representative of the organizations first by email and then by phone. HR representatives negotiated internally for participation in the study. They provided us with the email addresses of the employees to whom the electronic questionnaire was sent.

Company A is the Finnish subsidiary of a global provider of IT-consulting services, employing 560 persons at the time of data collection in Spring 2015. Main roles among individual participants were experts, service managers, project managers, a mixed role of those three, as well as back-office functions. Work in Company A consists of developing and maintaining in-house as well as external software systems. Customer relationships of Company A can be both long-term (several years) and short-term (a few months). The long-term customers may have legacy systems, the maintenance of which often requires special expertise that only a small number of (usually the older) employees have. Temporally the work is structured by projects, as well as by changes to relationships with customers and third-party stakeholders, who are often software developers from other companies for the same customer. The nature of tasks can vary and ranges from solving complex software engineering problems (several hours) to quick fixes of acute issues in a customer's system (15 min or even less).

Company B is an internationally operating Finnish provider of telecommunications and other online services, the back-office unit of which took part in our study. Company B employed about 2,500 employees in total at the time of data collection in Autumn 2015, while the back-office unit employed 105 persons. Main roles among individual participants included functions in finances and communications. Their duties consist of accounting, communications and marketing tasks, with the objective of serving the remaining organization, and their work is mainly reactive in nature. The activity of the back-office unit is temporally structured mainly around quarterly reporting seasons in a predictable manner, while sudden requests from upper management have to be resolved quickly in an unplanned manner.

4.2 Data collection

Data were collected using a short web-based weekly questionnaire which the participants were instructed to fill out every Friday before leaving work. Data collection took place over eight consecutive weeks, i.e. every participant handed in the weekly questionnaire at most eight times. Also, a few weeks prior to the main data collection period the participants completed an initial survey that was used to design the weekly questionnaire. This initial survey contained several of the questions later used in the weekly questionnaire, as well as questions about background information of the participants. In the weekly questionnaire we gave ready-made categorical alternatives to some of the questions that were open-ended in the initial survey. These alternatives were constructed from quartiles of responses given to the initial survey. (For example, an open-ended question about the number of colleagues in the initial survey was replaced with a question with the alternatives (0–6), (7–10), (11–19) and (over 19) in the weekly questionnaire of Company A.) This was done to keep the weekly questionnaire as simple as possible.

Table 3 shows the weekly questionnaire, together with the variables used in our analysis below. The questionnaire consisted of 11 questions that each concerns one of the situational features, including one for perceived level of interruptions.

Table 4 shows the number of participants who answered the initial survey, as well as the weekly questionnaires for both of the participating companies. In Company A we obtained 210 responses to the initial survey (the response rate: 37.5%), while in Company B there were 58 responses (the response rate: 55%). The number of respondents to the weekly survey varied between 81 and 139 in Company A, and between 36 and 52 in Company B. The total number of responses to the weekly questionnaire was 794 and 351 in Company A and Company B, respectively. In Company A we can observe a slow decline in response rate over the eight-week period, while in Company B the level of responses remains steady.

4.3 Weekly variation

First, we show that there is weekly variation in the responses given by the same participant. In the case of Company A, 140 participants, and in the case of Company B, 58 participants responded to at least two weekly questionnaires. Average numbers of weekly questionnaires filled by the participants were 4.8 (Company A) and 5.1 (Company B), respectively. Table 5 shows for every variable of interest both the number of participants who experienced no variation in the corresponding variable (Column DEV = 0), as well as the average standard deviation of the within-subject responses in those cases where this standard deviation was nonzero. We find that in all cases the majority of participants experienced variation in both perceived interruptions, as well as the situational features. Variation is somewhat lower in categorical variables, as expected.

4.4 Classification tree analysis

For the main analysis we use classification trees (Breiman *et al.*, 1984). A single observation in our analysis consists of responses to the weekly questionnaire by a given participant on a given

Instructions: We ask you to assess this week (Week xx) and answer this questionnaire on Friday or next Monday. It takes some 15 min to answer
- You can refer to the CTR report about this week when giving your answer (Company A)
- You can use different sources of information such as calendars, to-do lists etc. when giving your answer (Company B)

Interruption/ Situational features	Questions	Answering format Open-ended	Categorical
Interruption	Did you have to interrupt your task performance because of other intervening or urgent things this week? (almost never, rarely, sometimes, often and continuously)		x
Task	How many subtasks of different projects (e.g. testing and problem definition) did you have altogether under way this week?	x	
People			
Colleagues	With how many colleagues did you collaborate this week?		x
Customers/Partners	With how many customers/partners did you collaborate this week?		x
Teams	With how many different teams did you collaborate this week (e.g. project, service, marketing and virtual team)	x	
Technology			
ICT systems	How many ICT systems or software did you use this week (e.g. Microsoft Office and SAP)?		x
ICT problems	Did you experience any of the following ICT system related fault situations that prevented you from continuing with your tasks (yes/no) this week?		x
	Software is being updated		
	An existing system is replaced with a new one		
	A new system is taken into use		
	Interoperability problems		
	Access or authorization problems		
	Installation of new software		
	Service outage		
	Connection problems		
	Other problems		
Structure			
Projects	How many projects, processes or services did you have under way this week?	x	
Guidelines	To how many written guidelines did you rely on this week (e.g. documents, intra/Internet and policies)?		x
Meetings	How many meetings did you attend this week?	x	
Addresses	In how many different offices (addresses) did you work this week?	x	

Table 3.
Weekly questionnaire

week. The responses comprised 794 (Company A) and 351 (Company B) of such observations in total. The situational features are the independent variables, while the perceived level of interruptions is the class. Before fitting the model, we reclassified the original levels of interruptions ("almost never," "rarely," "sometimes," "often" and "continuously") to three classes (by merging "almost never" with "rarely," and "continuously" with "often"). This was done, because the more extreme classes had very few observations only. Model error is defined in the standard manner as the proportion of misclassified observations. (An observation is misclassified if the model assigns its level of interruption to an incorrect category.)

Table 4.
Number of responses over time

	Company A	Company B
Initial	210	58
Week 1	139	48
Week 2	118	51
Week 3	103	52
Week 4	92	36
Week 5	81	43
Week 6	95	38
Week 7	84	40
Week 8	82	43
Total Weekly	794	351

Table 5.
Statistics about temporal variation

	Company A		Company B	
Variable	DEV = 0	AVG DEV	DEV = 0	AVG DEV
Interruptions	29	0.69	11	0.67
Projects	13	1.89	3	2.59
Tasks	6	4.25	0	11.57
Meetings	4	2.42	1	3.07
Colleagues	50	0.61	15	0.68
Customers/partners	33	0.76	15	0.69
Teams	19	1.11	2	1.38
ICT-systems	36	0.59	22	0.59
ICT-problems	14	1.21	2	0.91
Addresses	44	0.62	28	0.64
Guidelines	44	0.67	5	1.15

Model selection was done using leave-one-out cross validation together with the One Standard Error Rule (see, e.g. Section 7.10 in Hastie *et al.*, 2009). That is, we chose the smallest classification tree for which the cross-validation error is within one standard error of the best performing model.

We assess goodness of fit by a pseudo-R-squared type of measure defined as 1-E/E_0, where E and E_0 are the classification errors of the found classification tree and an alternative model that always assigns every observation to the most frequently occurring class, respectively. This definition is analogous to the usual definition of R squared used, e.g. with linear regression models and can be interpreted in the same manner as the amount of variation explained by the model. That is, a model that has no explanatory power beyond the dummy model has R squared = 0, while R squared = 1 means that the model has perfect performance. All data processing, computing the classification trees and further analyses were carried out using R (R Core Team, 2018).

4.5 Interrupting situations identified by our approach

We continue by describing the obtained classification tree models. In Company A the classification error of the found tree is 0.44 (meaning roughly that the classification tree found assigns an incorrect level of interruptions to 44% of the observations) while a model that predicts a constant level of interruptions has error 0.54, resulting in a pseudo-R-squared value of 0.19. For Company B the numbers are 0.42 (classification tree error) and 0.60 (constant model error), respectively, giving a slightly higher pseudo-R-squared of 0.3. While these numbers are not perfect, they provide evidence that *we can identify situations that are* *associated with varying levels of interruptions using the selected set of situational features* showing this is the main objective of this study.

Next, we describe the decision trees in qualitative terms. For employees in Company A we identified seven different situations during the eight-week observation period, each having a different probability of occurrence of interruptions (Table 6). In four situations the probability to face interruptions "often" was 60–74% and in three situations 21–28%. Situations which carry a high probability to face interruptions are made up of a high number of tasks, ICT systems, meetings or colleague collaboration. Situations which carry a low probability to face interruptions have smaller quantities of those situational features. When facing interruptions "often," the respective situations exhibit a large quantity of at least one situational feature. When facing interruptions "sometimes" or "rarely" no situational feature appears in excessive amounts.

Likewise, in Company B we identified four different situations during the observation period (Table 7). In two situations the probability to face interruptions "often" was 63–74% and in two situations 7–15%. Situations which carry a high probability to face interruptions contain high levels of collaboration with colleagues or problems with ICT systems. Situations which carry a low probability to face interruptions had smaller quantities in those two features. When facing interruptions "often," the respective situations exhibit a large quantity of at least one situational feature. When facing interruptions "sometimes" or "rarely" no situational feature appears in excessive amounts.

4.6 Organizational interruption management by situations

Here we discuss how to interpret and utilize interrupting situations from our study. We assessed similarities of the situations from the two companies. In Company A the main feature in every situation is the number of tasks, and the first situation is characterized only by a high number of

Situations (the number of observations, total = 794)	Rule		Interruptions (%)		
	Features	Quantity (split points)	Often	Sometimes	Rarely
1. (243)	Tasks	> 13.5	68	26	6
2. (69)	Tasks	< 13.5	74	19	7
	and IT systems	> 12			
3. (22)	Tasks	< 13.5	77	18	5
	and IT systems	< 12			
	and meetings	> 16.5			
4. (58)	Tasks	< 8.5	60	26	14
	and IT systems	< 12			
	and meetings	> 3.5 and < 16.5			
	and colleagues' collaboration	> 10			
5. (147)	Tasks	< 8.5	28	44	28
	and IT systems	< 12			
	and meetings	> 3.5 and < 16.5			
	and colleagues' collaboration	< 10			
6. (82)	Tasks	> 8.5 and < 13.5	27	58	15
	and IT systems	< 12			
	and meetings	> 3.5 and < 16.5			
7. (173)	Tasks	< 13.5	21	29	50
	and IT systems	< 12			
	and meetings	< 3.5			

Table 6. Summary of seven situations in Company A based on classification tree analysis

Table 7. Summary of four situations in Company B based on classification tree analysis

Situations (the number of observations, total = 351)	Rule Features	Quantity (split points)	Interruptions (%) Often	Sometimes	Rarely
1. (94)	Colleagues' collaboration	> 20	68	28	10
2. (27)	Colleagues' collaboration	< 20	74	7	19
	and problems in IT systems	> 3.5			
3. (171)	Colleagues' collaboration	< 20	15	56	29
	and problems in IT systems	< 3.5			
	and meetings	> 3.5			
4. (59)	Colleagues' collaboration	< 20	7	30	63
	and problems in IT systems	< 3.5			
	and meetings	< 3.5			

tasks. Our assumption was that meaningful subtasks (as defined by Leavitt) consist of both primary and interrupting tasks. When the number of primary tasks is large, the number of interrupting tasks is large as well. Likewise, in Company B the main feature in every situation is the amount of collaboration, and the first situation is characterized only by a large number of colleagues. In both companies, the first situation also corresponds to a high level of perceived interruptions. When looking at the other situations that correspond to high levels of interruption, we find in both cases that it is enough for *only one* situational feature to appear in large amounts. The non-interrupting situations (5–7 with Company A and 3–4 with Company B), on the other hand, contain only conditions where the amount of *each* situational feature is small/moderate. These findings demonstrate that the sources of interruptions are diverse, and addressing only a single situational feature might not be sufficient for reducing interruptions in either of the companies. Taken together, the situations paint a more holistic picture of how the different situational features interact and result in interrupting vs non-interrupting conditions. In particular, these findings suggest that to avoid interruptions, work should be designed so that *all* situational features appear only in moderate amounts.

4.7 Limitations

We continue by discussing the limitations of our study. First, the weekly questionnaire we employed to collect data can only yield self-reported quantities that may be biased. For example, it is possible that respondents (unintentionally) overestimated some of the situational features during busy weeks when the number of interruptions was also large. Second, despite our efforts to make the weekly questionnaire easy to answer, some weeks a number of participants skipped the questionnaire. However, for this to have an effect on our main result (interrupting and non-interrupting situations were identified, the situational features thus carry some information about the perceived level of interruptions), the missing responses should have introduced artefacts in the data that erroneously lead to these specific classification trees being found. This, on the other hand, would require a very particular systematic reason for the missing responses. Third, we make no claims about causal relationships between the situations and interruptions. The situations only serve the purpose to give intuitive descriptions of the conditions the employees face. Fourth, we acknowledge that by considering only the amounts of organizational change elements, we lose possibly interesting information about, e.g. the intensity and nature of collaboration, the lengths of meetings, quality of interpersonal relationships, etc. However, given that our medium-term objective is to make use of trace data from ICT systems about the elements, taking this simplistic approach seems more promising, as this type of data is easier to obtain from said systems. Fifth, by choosing a time period length of one week we may have lost the possibly more fine-grained (hourly/daily) variation in interruptions. However, as our results suggest, aggregating the perceived level of interruptions at a weekly level (Luciano *et al.*, 2017) did result in interesting situations being identified.

5. Discussion

We began this study with the aim to extend interruption management from employee-level approaches toward the system-level by developing a data-driven approach and by demonstrating it with a simulation study. We now reflect on our process from and theoretical, practical and methodological viewpoints. First, we discuss, how a socio-technical approach goes beyond employee-level interruption management and enables to consider also other existing system models that may be helpful in the context of interruption management. One such model is coping with uncertainty. Then, we discuss insights for management practice using system-level handling of interrupting situations. The third viewpoint is methodological, where we argue that the developed data-driven methodology may be useful in general, and not only in the context of interruption management. This methodology includes challenges with a digital footprint to which we propose solutions.

5.1 Theoretical insights

With our simulation we are able to propose that interruptions at knowledge work are not only a matter between two employees or ICT and an employee. Rather, the occurrence of interruptions is related also to the socio-technical system of work. Next, we discuss, what may be interruption's role in the system using insights from Lyytinen and Newman (2008) using Leavitt's diamond. We also briefly address the role of uncertainty in the system beyond interruptions (Stock *et al.*, 2021).

5.1.1 Interruption's role in the system. Socio-technical thinking has assumed that a system will remain in balance due to low variation in its elements and their strong mutual interdependencies. When one element becomes inconsistent with others due to increased variation (e.g. novelty, malfunctioning, staff turnover and increased collaboration) an unbalanced situation emerges which is labeled a gap. A gap is any situation in the system that, if left unattended, will deteriorate the system's performance (Lyytinen and Newman, 2008).

Are the interruptions a sign of deterioration, or do they remedy situations of uncertainty where an employee quickly asks someone else for advice? From the system's viewpoint, such an advice or knowledge seeking interruption is more likely to sustain than deteriorate the system's performance. An advice seeker is an interrupter, a role also identified by Puranik *et al.* (2020). They propose that the needs of the interrupter are similar to those of the interrupted – to advance the work. In one moment, an employee may be the interrupter, and in the other moment they may be the interrupted one. However, there are disadvantages to interruptions (Puranik *et al.*, 2020), so it is justified to reduce their occurrence.

5.1.2 A role of coping with uncertainty in the system beyond interruptions. Attempts have been made to cope with uncertainty at a system level with various models since Galbraith (1974) and Stock *et al.* (2021) present a model which has similarities with our approach to identify interrupting situations. Uncertainty in the model of Stock *et al.* (2021) consists of four factors, which are similar to Leavitt's elements (presented by Lyytinen and Newman (2008)): unstable task requirements (task), uncertain techniques (technology), unclear product scope (people, structure) and large amount of effort to explain needed attributes (task). Stock *et al.* (2021) show that this kind of uncertainties creates needs to share knowledge. General knowledge sharing is not enough, but a more precise attention and identification of the need for knowledge is essential. They define three types of knowledge sharing needs: to share how to perform project tasks, to share valuable information, knowledge and skills and to share the need for specialized intelligence. The counterpart for requirements is knowledge sharing quantity (not too much or too little) for those three requirements by, e.g. communication structure (Stock *et al.*, 2021). They identify that uncertainties associate with interruptions, and handling them requires extra time. We go beyond this and suggest that future work should study if existing practices for coping with uncertainty can be also viable practices to reduce interruptions.

Next, we return to the socio-technical model that allows us to provide detailed advice on managing interruptions at the system level.

5.2 Interruption management at system level

Based on our results in Section 4, when there are fewer tasks and people, there are fewer interruptions. The example in Table 1 suggests that numbers in the task and people elements can be decreased by structural solutions, e.g. by preplanning and by preparing for change. Meetings as a structural feature have an important role in association to interruptions. While the number of meetings can of course be influenced directly simply by not scheduling meetings, we rather propose solutions that address the underlying needs to have meetings by addressing the task and people elements. Technology has the role in association to interruptions, but the role is somewhat different than in the task and people elements. We argue that tasks and people contain uncertainties that manifest as lack of detailed knowledge and that interrupting situations associated with tasks and people often generate new, interrupting tasks. But technology is predictable when fully adopted, and while issues with technology may halt the primary task, which can happen more often as the number of different systems increases, they do not necessarily generate additional tasks.

Our data-driven model can be helpful in maintaining a balance between the elements. It should be noted that not all tasks, people, meetings and ICT constantly involve the need to interrupt. But simultaneous increases in two or more elements are more likely to make the situation critical from the point of view of interruptions.

As the situations at an organization undergo unplanned and continuous changes, a means that provides visibility to the situations is needed. In this study we observed that the numbers of situational features about different elements may be a reasonable signal to follow. These contain enough information to devise structural actions that yield situations in which there is sufficiently detailed knowledge about how to carry out tasks which results in fewer interruptions.

The results of the simulation we presented above suggest that this approach may be feasible in practice. But getting information about elements directly from ICT systems is not straightforward which we discuss next.

5.3 Data-driven methodology

Interruptions in complex organizations are a continuously evolving phenomenon. Indeed, partly due to the proliferation of information systems across organizations and society, an increasing number of different phenomena are undergoing continuous evolution and change. This presents a challenge for static models that do not take the evolving nature of their subject into account. However, digitalization also potentially leads to large amounts of trace data about the phenomenon of interest being available from various sources. The approach discussed in this paper and demonstrated in the study may have applications also in other contexts with similar evolving characteristics.

5.3.1 Data-driven approach. In our study the theoretical framing was based on Leavitt's (1965) model of socio-technical change and the configuration theory (Meyer *et al.*, 1993). Classification trees were chosen as the analytics methodology because they are suitable for modeling complex phenomena, as well as easy to turn into interpretable descriptions of socio-technical situations unlike other black-box machine learning models. For data acquisition, we resorted to using a weekly questionnaire rather than actual trace data, as this study was intended as a lightweight demonstration of a data-driven approach to identify interrupting situations. However, the questionnaire was devised so that the resulting data have the same characteristics as real trace data. The simple situational features that we considered here (Table 2) could almost as such be calculated from data stored in various ICT systems. Real trace data might of course allow using an even wider range of more complex features (Crowston, 2017). These feature definitions may be based on theoretical frames as in our case, or be more data driven (Tonidandel *et al.*, 2016; Johnson *et al.*, 2019). While general epistemological issues of big data (Kitchin, 2014) are clearly beyond the scope of this paper, we advocate for the use of some theoretical framing when devising situational features. This allows us to connect possible data-driven findings with other results in a more disciplined manner and employ the approach as part of an inductive process as suggested by Tonidandel *et al.* (2016).

We argue that many relevant situational features can be obtained from various work-related ICT systems in (near) real time which is one of their major advantages over traditional survey instruments used for HR management (Luciano *et al.*, 2017; Crowston, 2017). For example, it may be possible to recognize critical situations for well-being and productivity in advance in a nearly automatic manner, and improve processes without time-consuming data collection from employees (Faraj *et al.*, 2018; Crowston, 2017). Next, we discuss a number of challenges that must be addressed to put such a data-driven approach into practice.

5.3.2 Challenges with digital footprint. As pointed out for instance by Angrave *et al.* (2016) and Rasmussen and Ulrich (2015), there are issues related to expertise and practices that have so far hampered the adoption of modern data science methods in the context of organizational management. As an example, our earlier discussion in Section 3 reflects the complexity of the ICT-system landscape and makes apparent that while evidence of situational features is present in systems, the systems are heterogeneous and often supplied by different vendors. A crucial ingredient of a system for a data-driven approach to management is thus an integrated data warehouse that aggregates relevant data sources. However, building such a data warehouse requires specialist expertise and can be difficult due to technical and regulatory constraints as well as organizational structures.

Certain data sources are restricted by regulatory constraints, the degree of which may depend on the jurisdiction. Email metadata is an example of such sensitive information. On the other hand, merely the number of different individuals an employee has been exchanging emails with may be less sensitive information and is thus potentially easier to use from a legal standpoint. As our study shows, simple amounts of various situational features are sufficient to model the level of interruptions. Resorting to such simple situational features may avoid some of the more major privacy issues and other regulatory constraints, although this should obviously be carefully considered on a case-by-case basis. Also, we point out that vast amounts of data, part of which are very sensitive, are already being collected and stored. The high-level question is thus how to make use of these data in a safe and compliant manner.

Despite the situational features we consider being simple; automatic data collection is also prone to errors and omissions caused for example by non-standardized usage patterns of the systems. Consider a software engineering team, where some team member separately documents every source code modification in a version control system, while another team member simply commits several changes at the end of the day in a single batch. In this case simply counting the number of times an employee has submitted changes to the version control system does not treat the two team members equally. The first one may seem to have completed several tasks, while the other has apparently only completed a single task, even though the actual amount of work might be much larger for the second team member. Such issues can to some extent be mitigated by common practices, as well as by making use of the available data in smarter ways. Also, we argue that for the purposes discussed in this paper the data need not be absolutely perfect, as long as their quality is "good enough," and possible error sources are known and their effects understood.

6. Conclusion

Interruptions are a common occurrence in knowledge work, and their management has so far mainly focused on employee-level approaches. In this paper we aim to go beyond this and propose considering the organizational level where the focus of management are the varying socio-technical situations in which interruptions occur. We devised an approach that builds upon Leavitt's (1965) socio-technical change elements (task, structure, people and technology) to identify these interrupting situations. We defined socio-technical change as varying situations which knowledge workers face in the same way they encounter interruptions. We then identify situations using situational features that represent Leavitt's elements, such as the number of tasks and projects an employee is associated with, the extent of collaboration an employee is engaged in and use of different ICT systems.

The study we present in this paper is intended as a demonstration of acquiring information about situational features using trace data from ICT systems. With the help of data-driven analytics, this would enable a near real-time monitoring and management of the changing situations in which knowledge workers operate. However, automatic data acquisition is in practice rather nontrivial and expensive. Hence, we conducted a "simulation" of this data-driven process by asking employees of two companies to provide similar information about socio-technical situations through weekly reports. We showed in our study that these situational features create situations that are associated with the perceived intensity of interruptions. Importantly, a classification tree analysis revealed that in both organizations the situational features can identify interrupting and non-interrupting situations of knowledge work. Next, we sum up theoretical and practical implications.

6.1 Methodological implications

The data-driven approach and analysis of classification trees in our method is agnostic w.r.t. the type of data. Any socio-technical feature of an organization that creates a situation for work and is measurable from trace data is a potential feature. Indeed, every organization has its own features in its own data, and the data-driven approach we propose is applicable to those. Our result is the data-driven methodology by which the interrupting situations can be discovered. Notably, the dependent variable can be other than a measure of interruptions. The same methodology can be applied to identify situations associated with also other aspects of knowledge work. Also, as many organizations were affected by COVID-19; steps were taken to accelerate digitalization, especially in what comes to remote collaboration. Thus, information about work and working conditions is increasingly available from ICT systems. However, while this study used relatively simple situational features, one could think of using a similar approach with more complex features. These could be the intensity of work, the sentiment of employees toward different aspects of their work (nature of tasks, colleagues, management, etc.), or features based on data from other sources, such as wearable devices or other self-tracking technology. The possibilities and challenges for these are interesting topics for further research.

6.2 Theoretical implications

Our study gives evidence that addressing interruptions at a system-level can be a meaningful research direction. The system-level opens up new research issues. Interruption's role in the system may be balancing (Lyytinen and Newman, 2008) or that of knowledge sharing (Stock *et al.*, 2021), but according to existing knowledge at individual level, interruptions are mostly harmful (Puranik *et al.*, 2020). Interrupting may be an indicator for one's need of knowledge, and upon receiving an answer, knowledge sharing for a specific need takes place. It may be possible to continue to study the conditions in the system so that a balance between the disadvantages and the benefits of interruptions for system and individual is found. The role of uncertainties beyond interruptions is a new hypothesis. Associations between uncertainty, knowledge and interruptions seem like an interesting avenue for future research.

6.3 Practical implications

Lastly, we sum up to four levels for interruption management practices from existing knowledge, from our study and from ideas for further research. First, current research focuses on how employees mutually agree good practices to interrupt each other and how to personally cope with interruptions (Puranik *et al.*, 2020). Second, currently automation is also being developed to identify suitable moments to interrupt the technology user (Anderson *et al.* (2021).

Third, in our study, the utilization of the socio-technical system approach with elements of task, people and technology (Leavitt, 1965) helped to identify situations that are associated with interruptions. In our simulation, out of the four elements, tasks and people have a central role in such situations. Practices for interruption management can be found in the structure, e.g. in ways to organize tasks and people to cope with unexpected changes, as demonstrated in the example (Table 1). Different actors in organizations can be responsible for elements, such as HR (people), business (task and people), organization (structure) and ICT (technology). Our model guides actors to follow all elements jointly.

The fourth level on interruption management continues at the system level. We hypothesize that beyond interruptions there may be situations with a degree of uncertainty about how, what, when and with whom to perform something. Hence one needs to seek advice and thus interrupts the other. For these situations Stock *et al.* (2021) develop a model of coping with uncertainty and propose knowledge sharing practices. However, the relationship between coping with uncertainty and interruptions needs further investigation.

From the data-driven theory development viewpoint, the most concrete next step is thus to carry out a variant of the study where self-reported situational features are replaced with trace data from ICT systems. This could also include experiments in which some other measure related to well-being, such as stress or recovery, is the dependent variable. Also, devising more sophisticated means to quantify the intensity of knowledge work from the digital footprint is an interesting question for future theoretical and practical work.

Finally, we want to emphasize that a system-level approach to interruption management is not something that should be left for management alone. Rather, we argue that by considering system-level solutions it may be possible also for employees to reduce the adverse effects of interruptions, that is, provided they are in a position to implement or suggest system-level changes to the way work is organized.

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Further reading

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