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Assessing the risks of service failures based on ripple effects: A Bayesian network approach

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ABSTRACT

This study responds to the need for assessing risks of service failures by focusing on ripple effects. We propose a Bayesian network approach to assessing risks of service failures based on the depdendence relationships among individual service failures. To avoid conceptual misunderstanding and imprecise use in practice, the suggested approach is designed to be executed in three consecutive stages: modeling a Bayesian network; assessing the risks in terms of probabilities of service failures (PSFs) and impacts of service failures (ISFs); and developing a service failure assessment map. A case study of the outpatient consultation service is presented to show the feasibility of our method.

1. Introduction

Assessing the risks of service failures has become strategically more important given the large scale and the increased complexity of service systems. It has become the norm for successful companies to consistently monitor the risks of service failures if they are to gain or maintain a competitive edge. Although the damages awarded in service failures vary across industries as well as context of service organizations, many studies have shown that service failures lead to customer dissatisfaction (Parasuraman et al., 1985), customer defection (Keaveney, 1995; Reichheld, 1996), and negative word of mouth (Richins, 1983). In this situation, service firms are focusing increasing attention on assessing the risks of service failures by defining service standards, establishing a monitoring process, training employees, etc. However, efficient and successful assessment is impeded in many cases by the absence of transparency as well as quality problems due to lack of quantitative and systematic methods (Mefford, 1993; Harvey, 1998). Consequently, recent years have witnessed a significant increase in attempts to use various models, methods, and tools to utilize existing engineering and technical know-how in the assessment of risks of service failures.

In this respect, numerous methods such as quality function deployment (Stauss, 1993), poka-yoke methods (Chase and Stewart, 1994), failure modes and effects analysis (Chuang, 2007), and fault tree analysis (Geum et al., 2009) have been employed. However, while they direct the ways by which we can evaluate the impacts of individual service failures or break a service process into simpler sub-processes, it has been pointed out that these are not useful in large and complex service systems due to lack of dependence relationships among individual service failures. A service process is composed of several components that impact each other in a particular sequence directly and/or indirectly. As a consequence, a service failure at a particular point of a service process can affect the occurrence of service failures at other points (referred to as *ripple effects* in this study) (Halstead et al., 1996; Chuang, 2007). For instance, it is possible that a potential failure point with low occurrence probability can have a significant impact on other failure points. Therefore, analyzing only individual service failures is insufficient; ripple effects among individual service failures should be taken into account at the system level.

To counter this problem, we propose a Bayesian network approach to assessing the risks of service failures based on the ripple effects. The primary strength of Bayesian network in service failure analysis lies in modeling and analyzing a large and complex service process that involves several dependence relationships and uncertainties. Firstly, in terms of the large scale of service systems, complex dependence relationships among individual service failures can be easily understood by representing them as a network topology, and can be measured in a quantitative manner. Secondly, with respect to the inherent uncertainties in service failures, various scenarios can be examined based on its ability to infer posterior probabilities. Finally, as far as the data availability is concerned, a Bayesian network is applicable to the service processes in which the objective data do not exist. In addition, a Bayesian network can be easily updated with new information about changes in service

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systems. Because of these considerations, the suggested approach is designed to be executed in three consecutive stages: service failure modeling, service failure analysis, and service failure assessment. First of all, potential failure points in a service process and their dependence relationships to each other are modeled as a Bayesian network. Second, the risks of service failures are examined in terms of the probabilities of service failures (PSFs) and the impacts of service failures (ISFs). Finally, a service failure assessment map is developed to facilitate effective understanding of the risks of service failures.

This study is unique and even exploratory in that the suggested approach is the first attempt that considers ripple effects in service failure analysis. It makes progress in the methodological investigation on service failures by not only introducing the concept of ripple effects but also suggesting substantial methods for reflecting the concept in assessing the risks of service failures. The suggested indicators mirror the ripple effects among individual service failures, thereby measuring the risks of service failures more accurately. Moreover, service failure assessment map can be useful in understanding the characteristics of individual service failures, and can offer implications for reducing the risks of service failures tailored to their characteristics. It is expected that our method can facilitate such decision making process as service redesign and resource allocation, and can serve as a starting point for a more general model.

The remainder of this paper is organized as follows. Section 2 presents the general background of service failures and Bayesian network. The proposed approach is explained in Section 3 and illustrated in Section 4 via a case study of an outpatient consultation service. Finally, Section 5 offers our conclusions.

2. Background

2.1. Previous studies on service failures

Although the literature varies in definition and scope, service failures generally encompass any situation where something goes wrong while service is delivered to a customer (Hart et al., 1990; Smith et al., 1999; Maxham III, 2001; Michel, 2001). The types and causes of service failures differ across industries, but it has been noted that service failures may cause significant damages to customer satisfaction (Parasuraman et al., 1985), customer retention (Keaveney, 1995; Reichheld, 1996), word of mouth (Richins, 1983), and ultimately hinder profitability of companies (Bejou et al., 1996). Numerous studies have been conducted to understand how to avoid service failures and minimize the adverse effect of them, which can be divided into two different streams based on the primary perspective: one is about post-failure activities for resolving the problems, and the other is about preventive efforts for identifying and analyzing current/potential service failures.

The first stream of research starts from the premise that service failures are inevitable due to the intensive human involvement in the service process (Hart et al., 1990; Mattila and Cranage, 2005). There exists an extensive body of literature on customer reactions to service failures and effective recovery strategies when service failures occur (Cranage, 2004; Michel et al., 2009). The common and frequently employed recovery strategies are apology, compensation, correction, managerial intervention, etc. (Bitner et al., 1990; Kelley et al., 1993; Tax et al., 1998; Smith et al., 1999). It has revealed that effective recovery strategies play an important role in achieving higher customer satisfaction (Tax et al., 1998; Smith et al., 1999; Michel, 2001), positive word of mouth (Maxham III, 2001), and customer royalty (Berry and Parasuraman, 1991; Keaveney, 1995; Maxham III, 2001).

Service recovery activities are crucial and imperative, but incomplete by themselves. Many researchers have pointed out that the preventive efforts should be incorporated for the following reasons. Firstly, recovering from service failures can be costly, and reducing the likelihood of service failures occurring in the first instance can be more beneficial (La and Kandampully, 2004). Secondly, service providers do not always get the opportunity to conduct service recoveries since they do not always realize that a problem has occurred (Society of Consumer Affairs Professionals, 1995). Finally, even well-managed recoveries cannot completely offset the negative effects of service failures (Firnstahl, 1989; Bolton and Drew, 1992; Hoffman et al., 1995; Kau and Loch, 2006). In particular, the more serious core-attribute service failures are, the more difficult recovering from failures is (Darida et al., 1996; Smith et al., 1999; Levesque and McDougall, 2000). Thus, service recovery strategies should be implemented in conjunction with preventive efforts for identifying and analyzing current and potential service failures (Halstead et al., 1996; Cranage, 2004; La and Kandampully, 2004; Kau and Loch, 2006; Chuang, 2007).

In recent years, recognizing the importance of preventive aspects, the second stream of research has been centered on providing methodological implications for analyzing service failures with systematic methods, to rectify the fundamental causes and prevent service failures. The following summarizes the major results of previous studies. Service problem deployment, a variant of QFD, was developed by Stauss (1993) for the transformation of problem information into prevention activities. Chase and Stewart (1994) provided a framework for systematically applying poka-yoke methods of total quality management (TQM) to the service context. FMEA has been utilized with the service blueprint to design failure-free service process (Chuang, 2007). Geum et al. (2009) proposed a service tree analysis approach based on the advantages of the original fault tree and appropriate modification for service process.

These methodological attempts have contributed to the systematization of analyzing service processes and assessing the risks of service failures by presenting coherent frameworks, but a lacuna still remains as to the consideration of ripple effects among individual service failures. So far, services have been viewed as interdependent interactive systems, not as groups of disconnected pieces and parts. In this vein, previous studies have identified that interdependence among the components of service systems is likely to form chains of service failures (Halstead et al., 1996). In particular, such ripple effects of service failures become a major concern of firms as services are becoming more complex and large-scale. However, most service organizations have been observed to make an effort to resolve problems at the local level when a service failure occurs (Lusch et al., 2007), which can lead to overlooking the ripple effects among service failures. Moreover, it has also been noted that methodological implications have rarely been investigated despite the importance of ripple effects among service failures to the assessment of risks of service failures.

2.2. Bayesian network

A Bayesian network is a directed acyclic graph that represents the probabilistic relationships among a set of random variables (Jensen, 2001). It consists of nodes, arcs, and probability tables. A node represents a random variable, and an arc asserts a dependence relation between the pair of variables. In a Bayesian network, nodes at the tails of the arrows and nodes at the heads of the arrows are called parents and children, and the states of the parent nodes affect the states of the child nodes. Each node is associated with a probability table according to its dependence relationships with other nodes. Nodes without incoming arcs, i.e.