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Predictive Analytics of Organizational Decisions and the Role of Rationality

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Predictive Analytics of Organizational Decisions and the Role of Rationality

by

Arash Barfar

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy
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DEDICATION

This dissertation, except for its shortcomings, is dedicated to my beloved father who always wanted me to become a university professor and no less, and my beloved mother who used to drive me to American English classes for years.
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Not only in this dissertation, but also for the rest of my academic life, I acknowledge my deep intellectual debts to professors Balaji Padmanabhan, Alan Hevner, and Terry Sincich.
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ABSTRACT

How can we predict key decisions made by organizations in the presence of big data and on-demand information? In this dissertation we exploit a large repository of B2B real-time transactional data with service quality indicators and present evidence that organizational decision analytics apply both rational and boundedly-rational (i.e. behavioral) economic models. The dissertation’s findings demonstrate that both utility and heuristic models, respectively, play significant roles in predicting organizational decisions on churn, a key decision in this context. In the presence of a large data set the assumed rationality of organizations appears to provide accurate predictions in uncontrolled experiences and selected boundedly-rational decision rules appear to cause somatic states that make organizations more sensitive to past total qualities of service. This dissertation makes significant new contributions to the understanding of how organizations can effectively use big data to make key operational decisions. As a managerial implication, organizations must be alert to heuristics that might exacerbate the impact of total service pain on customer's decision to churn.
CHAPTER ONE: INTRODUCTION

“We can’t solve problems by using the same kind of thinking we used when we created them.” Albert Einstein

“In scientific practice the real confirmation questions always involve the comparison of two theories with each other and with the world, not the comparison of a single theory with the world. In these three-way comparisons measurement has a particular advantage.” (Kuhn 1961, p. 184)

Service organizations are highly invested in maintaining strong relationships with their customer base, both individual customers (B2C) and business entities (B2B). Loyalty in B2B service operations is as important as in the B2C setting since the field is characterized by perhaps fewer customers but with more transactions and more revenue per transaction (Ruyruen and Miller 2007). Losing customers in B2B service operations is loss of steady large revenues that cannot be easily recovered due to the scarcity of similar prospects to acquire. Even low revenue business customers have the potential to grow rapidly into large, highly profitable businesses with significant service requirements.

While B2C service has received much attention, customer retention programs and specifically churn analytics have not been widely explored in B2B environments (Jahromi et al. 2014). As Wiersema states in the 2013 B2B Agenda Project report the unavailability of large databases of service intelligence has kept academics and practitioners from
leveraging analytics to scrutinize B2B churn. Wiersema (2013) further highlights the vital role of mining large databases to gain deep insights about customer experience and subsequently lower churn. To illustrate, a senior executive participating in the project states that “We want to ensure that we fully understand and focus on what really has an impact on customers. I think we could do that better—with greater granularity, faster, and more effectively. The question is How?” (Wiersema 2013, p. 484)

This dissertation is one of the first to investigate churn decisions in B2B service operations. In this vein, we highlight the virtues of theory-driven data analytics by employing a hybrid deductive/inductive approach to analyze and predict churn.

From the Service Operations Management (SOM) perspective, this dissertation focuses on one of the three major components of Roth and Menor’s (2003) proposed architecture for SOM research; i.e. “customer-perceived value of the total service concept.” Previous analytical, exploratory, and survey studies in B2C settings (e.g. Hays and Hill 1999; Keaveney 1995; Liu et al. 2011 respectively) have highlighted the role of service quality in loyalty. In B2B settings, too, survey and exploratory studies (e.g. Rauyruen and Miller 2007; Huntley 2006 respectively) demonstrate the role of quality in customer retention. We explore a large service intelligence database provided by a Fortune 500 company. This repository covers two years of weekly service transactions and eight important measures of (weekly) service quality for approximately one hundred thousand Small and Medium Enterprises (SMEs) as service customers.
The service quality indices in our database correspond to (the absence of) different service “hygiene” attributes (Naumann and Jackson 1999). Since the hygiene attributes (e.g. being on-time) are expected as inherent parts of the service, we suspect that the relevant service failures inflict pain on the customer SMEs. This observation involves economics and cognitive science contributing disciplines: Which measures of the past service pain can effectively connect the SME-perceived service quality to their subsequent decisions on churn? Should we assume that SMEs are run by an economic human who rationally considers the total pain to evaluate the service quality, or should we assume that a boundedly rational administrator (Simon 1997) employs heuristics to judge the past service pain—which makes the subsequent decision liable to different biases?

Studying heuristics and biases has been shown to be a promising direction for behavioral operations research (Bendoly et al. 2010; Gino and Pisano 2008). To illustrate, it has been demonstrated that customers’ satisfaction relies on what they remember from the service encounter (Bitran et al. 2008). Dixon and Verma (2013) have used an archival dataset and highlighted the role of sequence effects on customer subscription repurchase. Huang et al.’s (2013) model highlights bounded rationality in customers’ estimations of expected waiting time. Yet, such findings have been mostly confined to experimental or theoretical settings at the individual level (Bendoly et al. 2010). This dissertation is one of the first that investigates this phenomenon at the organizational level and in empirical settings using a large granular database. The use of cognitive science elements in an
empirical study is also a novel extension to the bodies of knowledge framework presented in Bendoly et al. (2010). With regard to the behavioral operations research typology suggested by Gino and Pisano (2008) this dissertation can be viewed as an adaptation/replication study.

1.1. Organizational Decision Making

Current thinking on the drivers of organizational decisions reflects two economic viewpoints. Behavioral economists view organizational decision making through the lens of bounded rationality, where information processing is affected by limitations on information, limitations on analytical processing capacity, and time limits (Sontheimer 2006). That is, even if the essential information is made available to a purposeful individual, her decisions will deviate from the optimizing ones. This phenomenon has been well demonstrated in research settings; that individuals are still susceptible to biases while evaluating accessible information (e.g. Zauberman et al. 2006). In the Heuristics and Biases Research Program— which is the most influential research program on human reasoning and decision making (Rieskamp et al. 2006), the Nobel laureate Daniel Kahneman, late Amos Tversky, and their colleagues have outlined a number of simplifying heuristics that guide human reasoning and at the same time make it susceptible to systematic errors (Gilovich et al. 2002). Such systematic errors are not confined to lay people; in fact, experts and professionals in different fields are prone to
make the same mistakes as well (for reviews see Frantz 2006). These experts presumably take the role of administrators in organizations (Simon 1997a), who according to Simon, are *satisficing* and not maximizing decision-makers (ibid). Leibenstein’s x-efficiency theory that addresses the inefficiencies in organizations’ internal activities is also based on the assumption that the basic organizational decision unit is the selectively (i.e. *boundedly*) rational individual—and *not* the organization (Leibenstein 1979). Similarly in their Behavioral Theory of the Firm (1992), Cyert and March suggested that organizations, like individuals, satisfice rather than maximize. Thus, it is not counterintuitive that today’s organizations are occasionally berated for not fully exploiting the information and evidence at their disposal prior to making important decisions: “If doctors practiced medicine the way many companies practice management, there would be far more sick and dead patients, and many more doctors would be in jail.” (Pfeffer and Sutton 2006).

At the other extreme, *neoclassical* economists postulate that organizations are rational, practically omniscient, and with no limitation on computational capacities and time (Rieskamp et al. 2006)—a corollary of their assumptions on *homo-economicus*. In response to behavioral economists that such postulates are *unrealistic*, the Nobel laureate Milton Friedman clarified that neoclassical economists do not insist that individuals behave rationally; what they do postulate, however, is manifested in Friedman’s “*as-if*” (Friedman 1953, p. 21): “… under a wide range of circumstances individual firms behave
as if they were seeking rationally to maximize their expected returns and had full knowledge of the data needed to succeed in this attempt.” That is, different individuals/ firms might behave in different erratic ways, but it is their assumed rationality (and not their erratic behavior) that helps economic theory yield accurate predictions about future group behavior (Friedman 1978, 1953).

Nonetheless, the Nobel laureate Herbert Simon (1997 a, p. 278) characterizes behavioral economics “not as a single specific theory but as a commitment to [i] empirical testing of neoclassical assumptions of human behavior and [ii] to modifying economic theory on the basis of what is found in the testing process.” The first part of the manifesto calls for an attempt to highlight any violation of the rationality assumptions i.e. “a search that can only succeed” (Smith 2003, p. 467) and has consistently resulted in a plethora of laboratory studies. In this sense and by virtue of laboratory evidences, behavioral economists have been capable of challenging these assumptions at the individual level (Sontheimer 2006), whereas the mixed findings in experimental economics (Smith 2003) have both contradicted and concurred with rationality. To illustrate, List (2004) demonstrates that “consumers with intense market experience behave largely in accordance with neoclassical predictions.” In the same vein, Nagarajan and Shechter (2013) have confirmed that Prospect Theory cannot explain the empirical data regarding the newsvendor problem.
Yet, the second part of the manifesto has not been researched as well as the first part especially in behavioral organizational economics. It has not been clearly demonstrated how the more realistic assumptions could strengthen the predictions about future organizational decisions. The need for this investigation was first highlighted by Simon (1979, p. 496); i.e. “Are there important, empirically verified, aggregate predictions that follow from the theory of perfect rationality but that do not follow from behavioral theories of rationality?” This question has not been thoroughly tackled in behavioral organizational economics research either (Katsikopoulos or Gigerenzer 2013) mainly due to the unavailability of organization level data (Camerer and Malemndier 2007). In line with this observation, Camerer and Malmendier (ibid.) accent the role of good data in behavioral organizational economics by highlighting the development course of behavioral finance. That is, behavioral research in corporate finance took off considerably later than that in asset pricing since obtaining organization-level or executive-level data has been more arduous than obtaining stock price data. Likewise, the advent of organization-level large data avails the probe into the behavioral organizational economics research. This is also vitally important in mainstream economics; as Friedman (1953) has accented the need for empirical evidence in both constructing hypotheses and testing their validity.

Thus, two fields have not been able to investigate one of their important research questions due to the unavailability of organization-level data. B2B service operations
researchers were not able to gain deep insights about customer experience and subsequently lower churn (Wiersema 2013) and behavioral organizational economics researchers were not able to demonstrate how the more realistic assumptions could strengthen the predictions about future organizational decisions.

With this contextual background in mind, in this work we explore a large service BI database provided by a Fortune 500 company to examine the predictive power of neoclassical and behavioral assumptions with regard to organizational decisions on loyalty. The database covers two years of weekly service transactions for nearly one hundred thousand Small and Medium Enterprises (SMEs) as service customers. As an SME makes service transactions with the service company its transactional profile is updated hypothetically by the instant service pain/utility that it just experienced. We note ‘hypothetically’ because as Jevons (1871) states in Theory of Political Economy (p. 11), “A unit of pleasure or pain is difficult even to conceive; but it is the amount of these feelings which is continually prompting us to buying and selling”—which is in line with Bentham’s Principle of Utility (1789). We hypothesize that the SMEs in this dissertation are active processors of service quality and constantly evaluate their service pain/utility profiles. Subsequently they decide whether to stop or continue their business with the service company. We draw on the economics and cognitive science literature to predict such decisions at the organization level.
Specifically, this dissertation examines the application of heuristic and utility models in predicting churn in a B2B setting. Despite its highlighted importance in behavioral operations and behavioral economics, the predictive accuracy of such models is rarely investigated in either of the fields (Katsikopoulos and Gigerenzer 2013). Yet, complications arise in analyzing large data (i.e. temporally extensive records of economic agents’ instant utilities) to inspect the evidence of rational/ boundedly rational decision making. To illustrate the problem space, please consider thousands of economic agents with hundreds of decision points, with different dimensions of decision space. In this dissertation we draw on the database and data analytics research to facilitate exploiting large data to investigate the processes of decision-making in organizations. Based on a unique and extensive empirical study at the organizational level the results offer some initial evidence— one of the first of its kind at the organizational level— in support of a broader quest to answer Simon’s question; i.e. “Are there important, empirically verified, aggregate predictions that follow from the theory of perfect rationality but that do not follow from behavioral theories of rationality?” —a question that “deserves a high priority in the agenda of management research.” (Simon 1997a) Moreover, the empirical study as described in this dissertation makes a clear contribution toward B2B service operations through understanding customer experience and subsequently lower churn.

It should be noted, however, that in this dissertation we examine the *procedural* rationality in organizational decision making, which addresses the quality of the processes
of decision in the organization (Simon 2000). One reason, in line with what Simon suggests in the psychology of administrative decisions (Simon 1997a), is that the actual decision on loyalty/churn intrinsically falls short of substantive rationality since it requires an accurate anticipation of the consequences that will follow on either decisions. And since these consequences lie in the future, they can only be imperfectly anticipated. In his Descartes' Error (1994, 2005), for example, the neurologist Antonio Damasio postulates that even with a lot of paper and a pencil sharpener, and a large desk, and nobody expecting us; (i.e. without the constraints of information and time), a decision that is free of intuition and emotions is almost unachievable.

Yet, procedural rationality has been examined from two different perspectives in psychology. The first is the Heuristics and Biases research program initiated by Daniel Kahneman and Amos Tversky and the second is the Fast and Frugal Heuristics research program led by Gerd Gigerenzer and his colleagues (Rieskamp et al. 2006). In the Heuristics and Biases research program, Kahneman and his colleagues basically set the neoclassical rational model of information processing as the benchmark and demonstrate that the use of heuristics and intuitions in information processing carries biases that make the reasoning susceptible to “severe and systematic errors” (ibid). At the other extreme and in the Fast and Frugal Heuristics research program, the benchmark is ecological rationality against which the use of heuristics and intuitions in information processing is essentially considered as optimal behavior. In fact, what is considered as rational
behavior from the neoclassical perspective might be viewed as irrational in the Fast and Frugal Heuristics research program (Altman 2006). Since we are investigating the information processing in organizations, we address bounded rationality as it has been endorsed by Kahneman and his colleagues in the Heuristics and Biases research program.

1.2. Churn Analytics

The idea behind the study in this dissertation was originated in the B2B service industry; i.e. how to predict a corporate customer’s decision on *churn* ahead of time in a way that the retention programs can be undertaken effectively. Churn is one of the subjects that have attracted considerable attention in predictive analytics, especially in telecommunications (e.g. Verbeke et al. 2012; Tsai and Lu 2009), financial services (e.g. Van den Poel and Lariviere 2004; Nie et al. 2011; Glady et al., 2009), electronic commerce (e.g. Yu et al. 2011), retail markets (e.g. Buckinx and Van den Poel, 2005), subscription services (Burez and Van den Poel 2007), and even donations (Fader et al. 2010) and employee churn (Saradhi and Palshikar 2011). From the machine learning perspective, several supervised and unsupervised techniques have been effectively applied to predict customer defection. For the most recent survey and comparison of machine learning techniques for customer churn prediction see Almana et al. 2014 and Vafeiadis et al. 2015 respectively.
The present dissertation contributes to the churn analytics literature in three ways. First, the majority of churn prediction studies are conducted in contractual settings where the timing of defection is clear. Yet, a significant segment of the service industry operates in non-contractual settings, where customers can respond, often silently, to multiple competitors’ loud overtures. Previous churn studies in non-contractual settings mostly adopt the “always a share approach” (e.g. Rust et al. 2011; Fader et al. 2010; Jahromi et al. 2014) and predict future customer behavior over a prediction period based on past behavior in a calibration period. However, defection timing is essential to investigate any connection between customers’ service quality assessments and subsequent decisions on churn. The present dissertation offers a unique approach to detect churn in noncontractual settings.

Second, the majority of churn studies incorporate (i) RFM (i.e. Recency, Frequency, and Monetary Value)-based factors, (ii) demographics, and (iii) customer surveys as the main ingredients of their predictive models (Buckinx and Van den Poel, 2005). In a more recent study, Benedek and colleagues (2015) have examined the role of customer’s social embeddedness in churn. There are few churn studies that use service quality attributes as potential predictors, and the few that do (e.g. Padmanabhan et al. 2011), have taken a purely inductive approach. To the best of our knowledge, the present dissertation is one of the first that apply the theories in cognitive sciences to set up predictive models for churn; an aspect of the dissertation that we refer to as theory-driven predictive analytics.
Third, the majority of the churn studies have been undertaken in B2C settings. That is, only a handful of studies have focused on churn in B2B contexts (namely Bolton et al. 2006, Jahromi et al. 2014; Chen et al. 2014). Bolton et al. (2006) conducted their study in a contractual setting environment with the data of 143 firms where “average engineer work minutes per contract” (p. 1816) represented the experience quality. In this dissertation, however, we investigate two years of eight weekly service quality indexes as momentary measures of service quality for nearly one hundred thousand SMEs. Jahromi et al. (2014) and Chen et al. (2014) both conducted their studies in noncontractual settings. Yet, the former defined churn as customer’s inactivity in the last 183 days of the data, and the latter defined it as customer’s inactivity in the last month. The present dissertation, however, is the only study in noncontractual setting where every churner has a specific churn date. Moreover, Jahromi et al. (2014) incorporated RFM variables as the study’s predictor variables. In the same vein, Chen et al. (2014) could not find any service quality variables among the top ranked predictors. On the contrary, the present dissertation demonstrates that merely service quality indexes can effectively predict corporate customers’ decisions on churn and loyalty.

1.3. Dissertation’s Potential Contributions and Structure

The present dissertation is an interdisciplinary study—centering around behavioral economics, neoclassical economics, neuroeconomics, psychology, clinical pain
studies, data analytics, and service operations— to shed some new light on predictive analytics of organizational decisions. To wit, we survey the findings related to the Heuristics and Biases program and the Fast and Frugal Heuristics program to investigate the role of heuristics and intuitive judgments in organizational decision analytics. This is also complemented by some stand-alone theories in psychology, as well as a number of findings in recent clinical pain studies. In tandem, we examine the role of the assumed rationality in organizational decision making— as a pillar of neoclassical economics. This will hopefully help us provide an answer to the question posed by Simon (1979) in his Rational Decision Making in Business Organizations: “Are there important, empirically verified, aggregate predictions that follow from the theory of perfect rationality but that do not follow from behavioral theories of rationality?” We suspect that the answer to this question does not have to be either-or; a combination of the findings from both schools of economics can yield an explanation for organizational decision making in practice.

As behavioral economics and neurosciences have recently partnered and given birth to “neuroeconomics”, we expand our survey to this new area in economics to see if we can draw on its implications in the context of organizational decision rationality. The neurologist Antonio Damasio’s somatic markers and homeostasis are two examples of the ideas in neurosciences that can be adopted in organizational decision making.

The IS dimension of this dissertation also concerns the contribution of data analytics to economics and decision making in a broad context— not just limited to
organizational decision making. To illustrate, big data can provide economists with extensive records of experienced utility and observed behavior which were deemed unattainable before; i.e. such extensive records cannot be attained in controlled experiments. Furthermore, eclectic data exploration and mining methods that are soundly tailored to answer relevant questions can contribute to the fields; especially behavioral economics that is low on rigidity, intolerance, and separateness (Tomer 2007). As an illustration, inductive methods may provide new insights on the orchestration mechanisms in the adaptive toolbox.

The rest of this dissertation is organized as follows. Chapter Two explains different manifestations of experienced utility and their roles in rationality. It also benchmarks the application of large empirical data sets against survey methods in capturing instant utility (i.e. the basic building block of experienced utility) and behavior. Lastly, this chapter concludes with materialization of experienced utility and observed behavior in the non-contractual setting of B-to-B service operations.

Chapter Three discusses the notion of adaptive toolbox and its potential role in organizational decision analytics. It essentially draws on behavioral economics and neuroeconomics to materialize an organizational adaptive toolbox; i.e. a set of different decision rules that can be applied in the context of B-to-B service operations to make decisions regarding loyalty and churn.
Chapter Four presents the methodologies for inspecting the empirical evidence of the exercise of different information processing models suggested by behavioral and neoclassical economics. It includes two main sections; i.e. descriptive and predictive analyses. Specifically, descriptive analyses are conducted to compare these heuristics decision rules as opposed to rational decision rules. Further, we conduct a series of analyses comparing the predictive accuracies of the competing models. A final predictive model reconciles the competing models and attempts to bridge the gap between the two perspectives. We conclude the chapter with sensitivity studies that verify the robustness of the findings.

Chapter Five pushes the dissertation essence to its apex; it highlights behavioral economics hypotheses that can only be tested with the state-of-the-art database algorithms. Specifically, it proposes an inductive framework for finding any evidence of employing adaptive toolbox orchestration mechanisms. Please note that the application of this inductive framework will not be limited to the organizational settings; it can also be applied in the context of behavioral decision making at the individual level. This, in fact, is a broader contribution of this dissertation since the orchestration mechanism in the adaptive toolbox is yet unknown in the Fast and Frugal Heuristics research program (Gigerenzer and Selten 2002).
Finally, Chapter Six concludes the dissertation with discussion of the findings, their implications for organizational decision analytics and B2B service operations, and the dissertation limitations.
“Any sound scientific theory, whether of time or of any other concept, should in my opinion be based on the most workable philosophy of science: the positivist approach put forward by Karl Popper and others. According to this way of thinking, a scientific theory is a mathematical model that describes and codifies the observations we make. A good theory will describe a large range of phenomena on the basis of a few simple postulates and will make definite predictions that can be tested. If the predictions agree with the observations, the theory survives that test, though it can never be proved to be correct. On the other hand, if the observations disagree with the predictions, one has to discard or modify the theory. (At least, that is what is supposed to happen. In practice, people often question the accuracy of the observations and the reliability and moral character of those making the observations.) If one takes the positivist position, as I do, one cannot say what time actually is. All one can do is describe what has been found to be a very good mathematical model for time and say what predictions it makes.” The Universe in a Nutshell, p. 31, Stephen Hawking

Jeremy Bentham (1789) interpreted utility in hedonistic terms, as a measure of pleasure and pain (Kahneman and Sugden 2005); an interpretation that became cogent among the nineteenth-century economics (Read 2007) and enticed Francis Edgeworth (1881, p. 101) into fantasizing “an ideally perfect instrument, a psychophysical machine [that] continually registers the height of pleasure [and pain] experienced by an
individual.” In the following century, however, economics moved into a new epoch of disenchantment with the Benthamite utility in the wake of a widely held belief that hedonic experience cannot be measured. This was a propitious time for neoclassical economists who assumed economic agents as rational utility maximizers to propound that decision utility, as inferred from the observed choice, can expound agent’s preferences (Kahneman and Sugden 2005). That is, since the substantive rationality was presupposed by neoclassical economists, further examination of procedural rationality and subsequently measuring instant experience were deemed purposeless.

Yet, these postulates have been questioned recently by behavioral economists. They have conducted different experiments that highlighted the individuals’ decisions that systematically fall short of maximizing future utility to demonstrate that individuals are only boundedly rational (Kahneman et al. 1997). They also argue that the presumption that hedonic experience cannot be measured might not be correct; that it can be viewed as a difficult technical problem but not a hopeless quest (Kahneman et al. 1997). In light of these counter-arguments and in a seminal paper, Kahneman and his colleagues (1997) resurrected Benthamite utility under the title of “experienced utility.”

Neoclassical economics assumes that consumers and organizations have complete access to all the information and analytical processing capacity that is necessary for making an optimal decision. Thus, rational models of information processing suggests that a past episode, as a bounded time interval defined by its content (Kahneman 2000),
should be evaluated based on the total experienced utility, which is the temporal integration or average of the episode’s instant utilities (Kahneman et al. 2003). Behavioral economists, however, would postulate that “the sovereign masters that determine what people do are not pleasure and pain, but memories of pleasure and pain.” (Kahneman et al. 1997, p. 385). With this statement, Kahneman and his colleagues (1997) are essentially addressing Bentham’s first words in The Principle of Utility (Bentham 1789, p. 1); i.e. “Nature has placed mankind under the governance of two sovereign masters, pain and pleasure. They alone point out what we ought to do and determine what we shall do; the standard of right and wrong, and the chain of causes and effects, are both fastened to their throne.”

The remembered utility in behavioral economics is liable to biases of memory (Kahneman et al. 2003) and hence is viewed as a fallible estimate of the actual experienced utility (Kahneman et al. 1997). This discrepancy may be referred to as the “memory-experience gap” (Miron-Shatz et al. 2009)— the existence of which is not stochastic; rather, it involves different kinds of systematic errors that are repeated by most individuals (Kahneman et al. 1997). The same argument applies to business and service operations, the focus of this dissertation, where it has been demonstrated that customers’ satisfaction relies on what they remember from the service encounter (for review see Bitran et al. 2008).
Despite the plethora of evidence in behavioral economics and psychology that individuals are often guided by their remembered utility while making decisions, we know little about this with respect to organizations. The information that an organization processes prior to making a decision is stored in the collective memory of its participants and to a greater extent, the artificial memory that consists of information systems (Simon 1997a). In behavioral economics, as discussed in the introduction, even presupposed easily available information does not guarantee rational processing of it since there are other constraints in place. To investigate the role of rationality in organizational information processing, the first step is capturing “instant utility” as the basic building block of organizational experienced utility (Kahneman et al. 1997, Kahneman and Tversky 2000), a topic we turn to next.

2.1. Instant Utility and Behavior: Surveys versus Empirical Data

In his Mathematical Psychics, Francis Edgeworth (1881, p. 101) fantasized a hedonometer as a “psychophysical machine that continually registers the height of pleasure experienced by an individual.” As a benchmark for the real measurement methods, the description of such “ideally perfect instrument” has two important elements: quantifying the exact amount of the instant utility as it is experienced by the individual at the moment, and repeating the process eternally. After a century of disenchantment with Behthamite utility and with the rise of behavioral economics,
individuals’ real experience/ behavior became an inseparable ingredient of the analyses in the field; highlighting the need for a real hedonometer. If such a hedonometer were in place, and had prolonged registering different types of utilities that thousands of people were momentarily experiencing, the streaming record would be in form of big data.

George Katona at the Institute for Social Science Research pioneered using survey methods to gather empirical data on consumers’ intentions and expectation (Simon 1997b), which has been recognized to have an important role in the development of the field (for reviews see Hosseini 2003). Two major survey methods have been proposed for recording instant utilities in psychology. Day Reconstruction Method (DRM) is designed to collect data describing a person’s experience in a given day by asking the subject to reinstantiate that day into her memory as a sequence of episodes (Kahneman et al. 2004a). However, its retrospective nature still makes it susceptible to recall biases. An alternative method that allows subjects to report instantly and repeatedly on their experiences in real-time and real-world settings is called EMA—Ecologically Momentary Assessment (Stone and Shiffman 1994). As reflected in its title, this method has been developed to strengthen ecological validity and attenuate recall biases, nominating it as the gold standard for measurement of instant utilities over extended periods of time (Kahneman et al. 2004b). Yet, again, it has been demonstrated that even the pain reported after a 20-minute operation is unduly influenced by recall biases (Redelmeier and Kahneman 1996); hence, instant reports in EMA do not guarantee immunity against systematic errors.
either. In sum, unless the EMA method involves cardiovascular or physiological monitoring, it shares the susceptibility to recall bias with DRM and any method that includes affective surveys. In line with this observation and being benchmarked against the Edgeworth’s hedonometer, recall biases emasculate the quantifying aspect of the survey methods.

Another issue with the EMA methods that makes them impractical particularly in organizational and service operations is that they carry a heavy burden of reporting instantly and repeatedly — as the second element of the Edgeworth’s hedonometer. That is, calling every customer or organization following every transaction is impractical. Furthermore, all affective survey methods carry the limitation of reactivity. In his chapter on objective happiness, Kahneman (2003) addressed a similar phenomenon under the heading of “focusing illusion”, where asking a question about a particular type of experience induces the respondent to focus on a special characteristic of that experience and that intrudes on her perception of the experience itself (Kahneman and Sugden 2005). These limitations make EMA methods impractical for recording instant utilities over prolonged periods of time (e.g. a year), which is necessary for answering the questions on the procedural rationality in organizations. For the similar reasons, Kahneman and Sudgen (2005, p. 173) highlight the need for “a method of measurement that elicits information about actual state of hedonic experiences, not attitude to issues or affective responses to transmissions.” This is especially important in the context of service
operations, where most of the studies asked respondents not only to retrieve but also to summarize their experiences with service companies in a non-real setting environment.

In line with quantification of instant utilities, we suspect that recording empirical data on the actual objective utilities that a person or an organization is receiving at the moment is a step towards actualizing Edgeworth’s hedonometer. The measures of physical magnitude of pain stimulus that Kahneman, Ariely and their coworkers used in their studies—such as loudness of an aversive noise (Schreiber and Kahneman 2000), water temperature (Kahneman et al. 1993), and thermal stimulus (Ariely, 1998) are examples for such actual objective experience. Kahneman and his coworkers argue that the functions that relate subjective intensity to objective measures are qualitatively similar for different people (Kahneman et al. 1997), leading to high correlations between self-reports and physical measures (Kahneman and Tversky 2000). In the context of this dissertation, the empirical data on service quality measures are a reasonable proxy for instant utility and its higher order constructs. Regarding the second element of Edgeworth’s hedonometer, such empirical data can be continually logged for large populations over prolonged periods—providing continuous accurate measure of utility which was deemed impractical by Kahneman and Tversky (2000).

Real observed data is not only vital with respect to gauging experienced utility in behavioral economics. At the other extreme also, Milton Friedman (1953) has highlighted the importance of real observed behavior of the firm; “what they do rather than what
they say they do.” (p. 31) In this sense, he stated that although questionnaire studies may be valuable in constructing hypotheses, they seem almost entirely useless to him as “a means of testing the validity of economic hypotheses.” (p. 31)

2.2. Observed Utility and Behavior in B2B Service Operations

The B2B service database at our disposal is comprised mainly of nine large tables on service transactions and service quality indices and one table on the SMEs demographics such as the age of the SME’s business relationship with the service company. It should be noted that the SME IDs are encrypted in the database at our disposal. The service transactions table includes the number of service units that each SME has been provided in each week within a two-year period. Nearly one hundred thousand SMEs each with approximately 105 weeks of service, the service transactions table has nearly ten million rows.

Moreover, the services company has defined a set of eight Service Quality Indexes (or SQIs), each corresponds a specific type of service failure that an SME might experience. Each of the eight SQI tables consistently has millions of <$SME\ ID, Service Week, Number of Corresponding Failures…$> tuples. Since there is no record registered for the weeks where there was no SQI specific failures in the SQI tables, we fill the corresponding weeks with zero failures in the relevant SQI tables. We cannot reveal the SQI names due to our confidentiality agreement with the service company.
Thus, for every customer at every given week, we know how many service encounters are subject to a specific type of service failure. Specifically, the SQIs correspond to the absence of different service “hygiene” attributes (Naumann and Jackson 1999). Since the hygiene attributes (e.g. being on-time) are expected as inherent parts of the service, the SQIs pertain to the different measures of physical magnitude of momentary pain stimulus \((p_t)\) that Kahneman, Ariely and their coworkers use in their studies (e.g. Schreiber & Kahneman 2000, Ariely 1998). In addition, since the SMEs simultaneously receive instant utility we proportion the weekly \(p_t\) related to each SQI with the number of service units in that week (i.e. proportional momentary pain, \(\tilde{p}_t\)). In addition to individual SQIs, we asked a domain expert in the service organization to propose a holistic SQI as a weighted linear combination of the individual SQIs. As SMEs make service transactions with the company their service pain/utility profiles become continually updated, hypothetically by \(p_t\) or \(\tilde{p}_t\) corresponding to different SQIs.

As organizational customers make service transactions with the company, their service pain/utility profiles become updated, hypothetically by \(\tilde{p}_t\). We note ‘hypothetically’, because as Stanley Jevons (1888) stated in his Theory of Political Economy “A unit of pleasure or pain is difficult even to conceive.” However, in the same paragraph he continues “but it is the amount of these feelings which is continually prompting us to buying and selling.” Likewise, we suspect that the organizations in this dissertation, as active processors of service quality, constantly process and evaluate their
service pain/utility profiles and based on that decide whether to stop or continue their business with the company. Consistent with the research questions of this dissertation, we are interested in using the customers’ service pain episodes to predict their decisions on loyalty: Should we assume that organizations practice a rational model of information processing where they make decisions based on a moment-based measure of experienced utility such as temporal average or integration, or at the other extreme, should we realistically presume that they are run by boundedly rational administrators who rely on judgment heuristics and intuitions?

To answer this question, we need first to define the concept of a service episode; i.e. a bounded time interval defined by its content (Kahneman 2000). Unless the SME’s loyalty age is less than two years we assume that the service episode starts with the beginning of our database. In the case of churners, the end of the service episode naturally coincides with the timing of defection; i.e. an observed behavior. Due to the non-contractual setting in this dissertation, ‘defection’ corresponds to a significant dormancy that lasts until the end of the two-year window. Considering the large number of SMEs (i.e. nearly one hundred thousand) and since non-contractual data do not come conveniently labeled or time-stamped, we employ the following two-step process, involving significant manual effort, to identify the churners and their corresponding timings of defection:
1. We first form a pool of potential churners including thousands of SMEs whose service unit time series satisfy the following two conditions:
   
a. The slope of the first order regression line on the number of service units against time is less than -0.05.

b. There is a point in time where the moving average of the number of service units drops by at least 80%. The two cutoffs (i.e. -0.05 and 80%) are selected since they carry a low rate of false negatives after cross-validating a random sample of candidates with the expert’s opinion in the service company.

2. For each candidate in the pool of several thousand potential churners, we plot the service unit time series and subsequently eyeball the time series manually for identification of churners.

In this process a few thousand SMEs are identified as churners and the timings of their defections are registered. This process took weeks of human labor and each time series identified as churn was verified by an expert in the company. Of the churning SMEs, we focus on those who had at least six months of transactions history prior to churn dates to ensure enough data from which inferences can be made. Each identified churner has its specific service episode with respect to the episode’s timings and content (i.e. instant service pains and utilities). Figure 1 shows a typical churner’s service episode.
In tandem, we implemented four algorithms for pinpointing the churn dates. A byproduct of the labor-intensive eyeballing process is a benchmark that allows us to compare the performance of these algorithms; i.e. finding the algorithm which functions more closely to a human expert in non-contractual settings. The four algorithms that have been implemented with dynamic SQL are:

**Algorithm 1.** Pick the date on which the *worst drop* in the service volume *moving average* has happened as the churn date.

**Algorithm 2.** First find the date on which the *worst drop* in the service volume moving average has happened. From that date, move *backwards* in time to find the first *right important* or the first *strict important* maximum in the corresponding time series. Pick the resulting point (which is essentially the *outset* of the worst drop in the service volume time series) as the churn date. The notions of *strict, left, right, and flat (important) extrema*
are adopted from the works of Fink and Gandhi (2011), where they use these extrema to compress a time series:

- \( V_t \) is a **strict** maximum if \( V_t > V_{t-1} \) and \( V_t > V_{t+1} \).

- \( V_t \) is a **right** maximum if \( V_t > V_{t+1} \) and there is an index \( left < t \) such that \( V_{left-1} < V_{left} = \ldots = V_{t-1} = V_t \).

- \( V_t \) is a **strict important** maximum if there are indices \( tLeft \) and \( tRight \) where \( tLeft < t < tRight \), such that:
  
  - \( V_t \) is strictly bigger than \( V_{tLeft}, \ldots, V_{t-1} \) and \( V_{t+1}, \ldots, V_{tRight} \), and
  
  - \( \text{Distance}(V_t, V_{tLeft}) \geq R \) and \( \text{Distance}(V_t, V_{tRight}) \geq R \), where \( R \) is a compression rate factor.

- \( V_t \) is a **right important** maximum if it is not a **strict important maximum**, and there are indices \( tLeft \) and \( tRight \) where \( tLeft < t < tRight \), such that:

  - \( V_t \) is strictly larger than \( V_{tLeft}, \ldots, V_{t-1} \),

  - \( V_t \) is not strictly smaller than \( V_{t+1}, \ldots, V_{tRight} \), and

  - \( \text{Distance}(V_t, V_{tLeft}) \geq R \) and \( \text{Distance}(V_t, V_{tRight}) \geq R \).

**Algorithm 3.** Pick the date on which the worst four-week drop in service volume in the service volume has happened as the churn date.

**Algorithm 4.** First find the date on which the worst four-week drop in the service volume has happened. From that date, move **backwards** in time to find the first **right** or
strict maximum in the corresponding time series. Pick the resulting point as the churn date.

All of these algorithms, including the Fink and Gandhi’s time series compression pseudo codes (ibid.) are implemented with dynamic SQL. Despite their one-line descriptions, the implementation with dynamic SQL involves significant lines of codes. Consider Algorithm 4 as an illustration: There are nearly 100,000 customers, each can have 105 weeks of service transactions. For each customer, and in each week, first we need to calculate and store the four-week aggregation of service volume starting from that specific week. Subsequently, we need to extract and store the differences of the adjacent four-week aggregations (i.e. four-week drops). Finally, we need to search for the week index that corresponds to the worst four-week drop. The corresponding dynamic SQL ETL including the Fink and Gandhi’s time series compression algorithm as the last step can be found in Appendix A. It should be noted that the distance function that we used in our dynamic SQL to implement the Fink and Gandhi’s algorithm is \( \frac{|a-b|}{|a|+|b|} \) and \( R \) (compression rate factor) is equal to 20%. Some of table names and fields in Appendix A are masked to respect the confidentiality agreement.

Benchmarking the churn dates that were extracted by the four algorithms against the churn dates that were proposed by the human expert revealed that Algorithm 1 functions more closely to a human: Algorithm 1 functions accurately for 62% of the churners; i.e. in 62% of cases the extracted churn date falls within a two-week interval
from the churn date that was pinpointed by a human expert. The second best performance (55%) belongs to Algorithm 2. The performances of Algorithm 3 and Algorithm 4 are 22% and 17% respectively. Again, it should be noted that in this dissertation we use the expert-identified churn labels and dates.
CHAPTER THREE: AN ADAPTIVE TOOLBOX IN ORGANIZATIONAL DECISION MAKING

“Nature has placed mankind under the governance of two sovereign masters, pain and pleasure. They alone point out what we ought to do and determine what we shall do; the standard of right and wrong, and the chain of causes and effects, are both fastened to their throne.” Bentham (1789, p. 1)

Based on the Principle of Utility expressed in the above quote, we posit that the service pain a SME experiences can be used to predict its future decision on loyalty and churn. Yet, which measures of the past service pain can predict the subsequent SME’s decisions on churn? Should we assume that SMEs are run by an economic human who is omniscient and rationally considers the total pain to evaluate the past service quality, or should we assume that a boundedly-rational and satisficing administrator (Simon 1997a) employs heuristics to judge the past service pain?

Omniscient rational models of information processing suggest that past service episodes should be evaluated based on the total experienced service pain which is the temporal integration or average of the episode’s instant pains. Behavioral economists, however, would postulate that “the sovereign masters that determine what people do are
not pleasure and pain, but memories of pleasure and pain.” (Kahneman et al. 1997, p. 385) Such remembered utility is liable to biases of memory and hence is viewed as a fallible estimate of the actual experienced utility; a memory-experience gap. (Miron-Shatz et al. 2009) Behavioral economists propose a variety of heuristic decision rules that reflect such biases and memory-experience gaps.

In the context of bounded rationality, the adaptive toolbox is a metaphor referring to a collection of fast and computationally cheap heuristics and intuitive decision rules (Gigerenzer and Selten 2002) as opposed to the rational model of decision making. The decision rules in the adaptive toolbox are hypothetically invoked when at least one of the information processing constraints, namely limitations on information, limitations on analytical processing capacity, and time limits is in place. That is, given these constraints, rational measures of information processing such as temporal integration or average of instant utilities are not easily available to conscious awareness (Kahneman et al 2003); hence, people rely on the decision rules in the adaptive toolbox. Although the application of these decision rules is quite useful in alleviating the constraints (i.e. ecological rationality), they carry certain biases that lead to systematic errors. Consistently, the decision rules in the adaptive toolbox are not expected to yield optimizing decisions as it is intended with rational models of information processing (Sontheimer 2006).

In line with the goal of this dissertation, we first need to postulate an adaptive toolbox that consists of the organizational decision rules for defection based on the
service pain/utility that an organization has received from the service company. The basis of this adaptive toolbox is the main findings in the Kahneman and Tversky’s heuristics and biases program — as the most influential research program on human reasoning and decision making (Rieskamp et al. 2006). In this program, Tversky and Kahneman (1974) explained an extensive list of relevant norm violations in terms of three general heuristics, namely representativeness, availability, and anchoring and adjustment. Later on, an affect heuristic replaced anchoring and adjustment in this list (Kahneman and Frederick 2002).

The decision rules in the adaptive toolbox will be mainly proposed based on the representativeness and availability heuristics as the focus of the heuristics and biases program (ibid). Kahneman (2000) hypothesized a psychological process called “evaluation by moment” that explains the construction of remembered utility of a temporally extended experience such as the one in organizational service operations. According to this hypothesis, individuals evaluate their past episodes of experience by constructing a representative moment and subsequently evaluating the utility of that moment (Kahneman and Tversky 2000; Kahneman et al. 2003). Kahneman posits that the same heuristic is applied in a slightly different way to form decisions about the future outcomes. The “snapshot model” (Fredrickson and Kahneman 1993) that explains how this hypothesis is applied to the retrospective evaluations of the past episodes asserts that human beings evaluate their past episodes of experience by constructing a representative moment and subsequently evaluating the utility of that moment (Kahneman et al. 2003).
That is, they continuously construct an affective commentary by updating the snapshot (not film) of those representative moments (Fredrickson and Kahneman 1993; Kahneman and Tversky 2000; Kahneman et al. 2003). These composite snapshots are hypothetically constructed using the representativeness and availability heuristics and are going to be evaluated in lieu of the temporal integration of instant utilities in the whole episode. As a result, the temporal dimension of the organizational service experience is neglected (Kahneman 2000), leading to systematic deviations from logical analysis of service quality.

In the context of service operations, organizations can be viewed as patients with chronic pain stemming from different lapses in ongoing services. Since their first transaction with the service company, these “active processors of information” (a notion proposed by Turk and Rudy (1992) for patients with chronic pain) have been continuously updating their snapshots, based on the streaming experiences with the service provider. Consistent with the snapshot model, they subsequently use the characteristics of the latest snapshot in their memories to evaluate their past episode of experience with the service company (Varey and Kahneman 1992; Frederickson and Kahneman 1993; Kahneman et al., 1993; Stone et al. 2000;).

Unlike patients, however, organizations are not passive and are presumably able to end the service pain instantly by switching to a different service provider. Thus, such evaluations are hypothetically important determinants in deciding whether to defect
from the service company and end the chronic pain, or stay in business with them. Hence, the ideal snapshot that we should investigate to answer this dissertation’s research questions would be the last one in the customer’s memory before her defection from the service company. That is, we use the timing of the organization’s overtly expressed choice to anchor to the last snapshot in its memory. Examining the service/ pain profile corresponding to this snapshot can shed light on the mental model the organization employed before switching providers.

The affect heuristic (Slovic et al. 2007) can partly explain the exercise of the adaptive toolbox in making organizational decisions on defection. It postulates that the current affect influences judgments and decisions (ibid). This is in line with Antonio Damasio’s somatic marker hypothesis, according to which “when a negative somatic marker is juxtaposed to a particular future outcome the combination functions as an alarm bell.” (Damasio 1994, 2005). Consistent with the affect heuristic, when the conditions of a decision rule hold, it can set off an alarm about the future service quality, and the organization might churn mainly due to the biasing nature of that alarm bell.

For exposition, for each decision rule proposed in the adaptive toolbox we illustrate an actual example from the data that is consistent with that rule. By ‘consistent’, we mean that the data behaves as if a customer employed this decision rule and churned consequently. Of course, not seeing other controls or factors makes it impossible to show causality; however, we still sought such examples in the data for two reasons. First, such
examples help the reader potentially see the impacts of an adaptive toolbox with such rules on B2B churn. Second, any rule in the toolbox should have at least some examples in the big data to be considered part of the toolbox. Not seeing any example may suggest that the rule is in fact never employed and should not be part of the toolbox.

3.1. Representativeness Heuristic Decision Rules for Churn

A prominent heuristic that is often employed to judge an episode of experience is called the peak-end rule (Fredrickson and Kahneman, 1993), where an individual evaluates a past episode of experience based on its maximum instant utility along with a value close to the end — as the two representatives for all instant utilities included in the episode. Redelmeier and Kahneman (1996), for example, show that among a group of patients undergoing a painful operation (e.g. colonoscopy), those who had less pain at the end of the operation evaluated the whole procedure less painful than the ones with more intense pain at the end, although the actual total pain that the former group had experienced was considerably less than the total pain for the latter. The evidence of the peak-end rule application has been demonstrated in various experimental settings for short and extended episodes and has been shown to account for over 80% of the systematic variance in several studies (e.g. Varey and Kahneman 2006; Schreiber and Kahneman 2000; Ariely 1998; Kahneman et al. 1993).
The original peak-end rule heuristic is solely an average of the most intense pain in the episode and the pain experienced near the end of that episode. That is, the timing of the peak pain does not matter in the subsequent evaluation. This may not be important in 4 to 67-minute episodes in the Redelmeier and Kahneman’s study (1996); however, we suspect that the peak pain timing plays an important role in long episodes like the ones in the context of the present dissertation that can extend over 18 months. This is aligned with the construal level theory in psychology (Trope and Liberman 2003) according to which people may find distal objects and events more abstract than proximal ones. In the same vein, some studies highlight the role of slope and velocity of the trend of instant pains (for reviews see Ariely and Carmon 2003) where a sequence of increasing momentary pain is retrospectively judged worse than a sequence of decreasing one, even though both sequences deliver the same total pain. That is, in any pain profile, pushing the peak pain to the end of the episode can change the slope significantly, whereas the peak-end average stays as before. For these reasons, we propose different decision rules based on the end pain and the peak pain separately.

The first and simplest decision rule (DR1) is solely based on the end service pain. That is, the organization will defect if the instant service pain is greater than zero, regardless of its magnitude. Apparently, if the organization employs this decision rule and churns, the last instant pain that they experienced becomes their end pain.
The first and simplest decision rule (DR1) is solely based on the end service pain. That is, *the SME will defect if the instant service pain is greater than zero, regardless of its magnitude*. If the SME employs this decision rule and churns, the last instant pain that it experienced becomes its end pain. Figure 2 depicts a churn in the service database that can be attributed to the application of this decision rule; i.e. the SME decides to churn the first time that there is an incident of a specific service failure. To formulate decision rules in a way that allows us to investigate their application in the database, we consider a six-week response window as the time in which an SME needs to act upon the alarm that a specific heuristic has set off. That is, the SME presumably needs some time to act upon its decision and to complete a switch to another service company. Consistent with the six-week response window, DR1 can be formulated as:

**DR1**: churn in week $T$ if $\exists t \in [T - 5, T]: \overline{p}_t > 0$;
DR1 can also have a rational manifestation if the idea of extensional target evaluation is embedded — where organizations’ tolerance for service failure grows as the overall scope of service (e.g. overall number of packages shipped throughout the transaction history) increases. It should be noted, however, that although it has been stressed in the literature (Kahneman and Frederick 2002) that the logical rule of judgment is extensional, no such strict statement can be made in the context of this dissertation; i.e. it is not clear whether the potential insensitivity to scope is an unconscious effect or a deliberate strategy. The reason is that organizations, compared to individuals, are more likely to have logged information about the scope of their transactions with the service company; hence, the extensional target attribute is presumably not low in accessibility. Moreover, here both sensitivity and insensitivity to scope are backed by apt explanations: in one scenario, an organization may not take her broad scope of service transactions into account — expecting no service pain at all, since she is paying for each unit of service. Some may even push this further — expecting that broader scopes of service transactions deserve special care from the service company and subsequently less incurred pain. We refer to this hypothetical phenomenon as righteous neglect of scope — since it can be endorsed by analytic reasoning. At the other extreme, however, an organization may appreciate the utility and probability — admitting the fact that as the service scope expands, the probability of service failure of any kind grows — leading to sensitivity to the overall scope. For the same reason, in addition to instant proportional pain ($\bar{p}_t$) we
will test all of the suggested decision rules with instant pain (denoted by \( p_t \)) as well; i.e. without considering the instant service utility that an organization received.

The decision rule for extensional evaluation of the end service pain should be proposed in a way that satisfies *monotonicity* (Ariely and Lewenstein 2000). In the context of service operations, monotonicity holds if each service unit adds to the service failure tolerance threshold an amount which depends on the previous number of service units provided to the organization and also the service failures they have already experienced. In case of prototypical judgment, however, no such correlation is expected. To illustrate, suppose that throughout the past course of service transactions where 1000 units of service were provided by the service company, the organization has incurred ten units of failure in total. In the present month, the number of service units is 101 and the organization has experienced one unit of service lapse. If this organization relies on prototypical judgment, this additional unit of failure in the present month strikes her as an increase in the total service pain— an evaluation that could result in defection as a prudent response through DR1. In the same scenario and in case of extensional evaluation where the organization *rationally* keeps a sense of proportion, one unit of pain is commensurate with 101 units of service, compared to the past proportional negative utility (i.e. 10/1000). The organization may even interpret this in part as a plausible sign of improvement in the QoS— perpetuating her business with the service company.
Consistently, the decision rule for extensional evaluation of the end service pain (DR2) states that the SME will churn if the updated overall average of instant service pain (updated after the most recent service lapses) is greater than the same measure prior to the recent service failures. This condition holds iff the average of the recent instant pains is greater than the same measure prior to the recent service failures. In Figure 3, for example, the service pain in the red area could cause an SME with a sense of probability to churn, although it is not worse than the pain the SME experienced before. The reason is that the new average pain (red area) is worse than the previous average pain (gray area) — which can be interpreted as a decrease in the quality of service.

**Figure 3**: Application of DR2; (a) Service failures (b) Transaction volume

**DR2**: churn in week $T$ if 
\[
\frac{\sum_{t=T-6}^{T} p_t}{\sum_{t=T-6}^{T} u_t} > \frac{\sum_{t=1}^{T-6} p_t}{\sum_{t=1}^{T-6} u_t},
\]
where $u_t$ is the volume in week $t$.

A question at this point concerns the roles of $p_t$ and $\bar{p}_t$ in DR2 implementation; i.e. if the decision rule projections with $p_t$ and $\bar{p}_t$ are essentially different. To address this concern, let us suppose that there are three weeks of delivery. Moreover, suppose that in
these pain/utility profiles each week is denoted by a fraction where the numerator is the number of a SQI failures, and the denominator is the number of service units that were provided under the corresponding insurance. The following two pain/utility profiles explain the difference of projecting $\frac{\sum_{t=T-2}^{T} p_t}{\sum_{t=T-2}^{T} u_t}$ with $\bar{p}_t$ versus $p_t$:

- **Scenario i:** $\frac{2}{3}, \frac{2}{4}, \frac{1}{2}$:
  $$\frac{\sum_{t=T-2}^{T} p_t}{\sum_{t=T-2}^{T} u_t} = \frac{2+2+1}{3+4+2} = 0.55556$$  whereas  $$\frac{\sum_{t=T-2}^{T} \bar{p}_t}{\sum_{t=T-2}^{T} u_t} = \frac{\frac{2}{3} + \frac{2}{4} + \frac{1}{2}}{3+4+2} = 0.18518$$

- **Scenario ii:** $\frac{2}{3}, \frac{3}{5}, \frac{0}{1}$:
  $$\frac{\sum_{t=T-2}^{T} p_t}{\sum_{t=T-2}^{T} u_t} = \frac{2+3+0}{3+5+1} = 0.55556$$  whereas  $$\frac{\sum_{t=T-2}^{T} \bar{p}_t}{\sum_{t=T-2}^{T} u_t} = \frac{\frac{2}{3} + \frac{3}{5} + \frac{0}{1}}{3+5+1} = 0.1407$$

It is notable that the DR2 implementation with $\bar{p}_t$ captures the difference between the two pain/utility profiles.

The last decision rule in this section addresses the peak aspect of the peak-end rule— where a SME might take the maximum instant (proportional) service pain as a representative for all instant (proportional) pains and subsequently judge the episode based on that. The decision rule (DR3) addresses an SME that will churn if the most recent instant (proportional) pain is greater than any instant (proportional) pain it has experienced so far. Figure 4 depicts a churn in our database that can be attributed to the application of the peak service pain decision rule.
Benchmarked against the first 6 months of the available data (gray area; \(\bar{p}_t = \frac{1}{4}\)), the SME does not churn in the green area since the corresponding service pain is not the worst pain it has ever experienced (\(\max(\bar{p}_t) = \frac{1}{7} < \frac{1}{4}\)). In the red area, however, the SME decides to churn the moment this specific service pain gets exacerbated (\(\max(\bar{p}_t) = \frac{3}{11} > \frac{1}{4}\)).

**DR3:** churn in week \(T\) if 
\[
T = \max \left\{ t \mid \bar{p}_t > \frac{T-6}{T-1} \max(\bar{p}_t) \right\}
\]

### 3.2. Availability Heuristic Decision Rules for Churn

In accordance with attribution theory, we suspect that the SMEs' judgment about the service failure frequency is a determinant of their decisions on loyalty. That is, frequent service lapses eventually turn into a stable attribution of the service company — pertaining to the application of a judgment heuristic known as the “availability
heuristic.” An incident is estimated as frequent if it is available; i.e. it can be easily brought to mind. (Tversky & Kahneman 1973) In clinical studies, for example, it has been shown that the recalled pain frequency is often overestimated if the pain is recent. (Van Den Brink et al. 2001, Shiffman et al. 2008)

In service operations, the broad decision rule stemming from the availability heuristic is equivalent to DR1. That is, if the most recent service pain is greater than zero, the service failure that caused pain will be also conceived as frequent — an impression that can lead the SME to churn in accordance with attribution theory. As noted earlier, this broad decision rule covers both prototypical and extensional target evaluation. Here, however, we present the manifestation of this decision rule for the extensional evaluation of frequency with two different measures.

The first measure for service failure frequency is temporal \( f \), which is the number of weeks that include at least one incident of related service failure divided by the number of weeks that include at least one service unit (i.e. utility). That is, \( f = \frac{|\{t | \forall t \ p_t > 0\}|}{|\{t | \forall t \ u_t > 0\}|} \).

Following the same logic presented for DR2, the decision rule for extensional evaluation of temporal frequency (DR4) is that an SME will churn if the current temporal frequency of service failure is greater than what it was before the service failures. Figure 5 depicts an incident where churn is subsequent to two consecutive service failures.

**DR4:** churn in week \( T \) if \( \frac{\sum_{t=T-5}^{T} f}{T-5} > \frac{\sum_{T}^{T-6} f}{T-6} \)
The second measure for failure frequency is *incidental* \((F)\), which is equal to the number of service failures divided by the number of weeks that include at least one service unit—\(F = \frac{\sum pt}{|\{t| \forall t, u_t > 0\}|}\). Figure 6 depicts a churn that can be attributed to the application of the availability heuristic with the incidental measure.

**DR5:** churn in week \(T\) if \(t=7-5F > T-6F\)

**Figure 5:** Application of DR4; (a) Service failures (b) Transaction volume

**Figure 6:** Application of DR5; (a) Service failures (b) Transaction volume
3.3. Somatic Markers for Heuristic Decision Making

In his *Psychology of Administrative Decisions*, Simon (1997a, p. 137) speculates that “there is a continuum of decision-making styles involving an intimate combination of the two kinds of skill (i.e. intuitive and analytical).” In a similar vein, he views emotions as “a force that helps direct actions toward particular goals by holding attention on them and the means of their realization.” (p. 91) This view is in line with Kahneman & Frederick’s (2002) assumption regarding the dual-system of cognitive processes in the context of organizational decision-making. That is, System 2 (i.e. reasoning) concurrently monitors the quality of the quick proposals made by System 1 (i.e. intuition) and subsequently endorses, corrects, or overrides them. Given these observations, we suspect that the boundedly-rational heuristics can also play the role of a mechanism that draws SMEs’ attention to the rational measures of service quality.

Among the relevant theories in cognitive science, the *somatic marker hypothesis* in neuroscience (Damasio 1994, Bechara & Damasio 2005) can explain the hypothesized synergy between rational and boundedly-rational assessments of service quality in organizational decision-making. In this sense, a somatic state in a SME caused by a heuristic (e.g. peak service pain) “functions as an alarm bell” and “operates not only as a marker for the value of what it represented, but also as a booster for continued working memory and attention.” (Damasio 1994, p. 198) That is, the biasing nature of heuristics might cause a somatic state which draws the organization’s attention to the service
quality and subsequently calls for reasoning and judgment— which might be carried out using the rational measures of service quality assessments.
“Nature undoubtedly responds to the theoretical predispositions with which she is approached by the measuring scientist. But that is not to say either that nature will respond to any theory at all or she will ever respond very much.” (Kuhn 1961, p. 176)

In this chapter we analyze the temporally extensive data on organizational service quality and behavior in order to inspect the predictive accuracies of the utility and heuristic models: To predict organizational decisions on churn and loyalty, shall we assume that the SMEs in this dissertation would apply any of the decision rules in the adaptive toolbox, or at the other extreme, it is as if they would employ a rational measure (e.g. temporal integration of service pain/utility) to evaluate their past experience with the service company? Or, as Simon speculates in his 1997 commentary on The Psychology of Administrative Decisions (Simon 1997a, p.137); “there is a continuum of decision-making styles involving an intimate combination of the two kinds of skill”.

We begin by scrutinizing the importance of the adaptive toolbox decision rules and the rational model of information processing in organizational decisions on churn. Since we are investigating the effectiveness of ideas in behavioral economics, we refrain
from rushing into the tests of statistical significance (but we will of course focus on this when we discuss findings from the predictive perspective). One reason is that initially, behavioral economics was partly defined in terms of “a rejection of positivism as the methodological foundation for economic research.” (Hosseini 2003, p. 394) Economists like McCloskey support this rejection by arguing that “statistical significance is neither necessary nor sufficient” for economic importance. (Ziliak and McCloskey 2008, p. 27) Consistent with this point of view, lack of fit of a model that consists of the adaptive toolbox decision rules will not necessarily indicate that such decision rules are inconsequential. It is noteworthy, however, that this does not make economists like McCloskey against quantitative analysis— which is the focus of this section. In fact, her book “Bourgeois Dignity: Why Economics Can’t Explain the Modern World” (2010) is a quantitative book, yet without any test of statistical significance.

In line with this, we first conduct a series of descriptive analyses where we explore the empirical data subsets for any evidence of applications of the adaptive toolbox decision rules— that can corroborate their importance. To wit, we will analyze a subset of the temporally extensive data to check whether more churners, compared to nonchurners, have had an alarm set off by a specific decision rule for at least once before their decision on defection. In the same vein, we will make a comparison to see whether a specific alarm was set off more frequently for the organizations that have churned, compared to the ones that are still in business with the service company. Finally, we will
extract a ratio which allows us to investigate the application of different decision rules right before defection. We will close the descriptive analysis subsection with a comparison between the actual temporal average of service pain/utility that the churners and nonchurners have experienced— as a likely measure in the rational models of information processing.

Following the descriptive analysis, we proceed to the tests of statistical and practical significance as the cardinal method of theory appraisal in mainstream economics. That is, in “The Methodology of Positive Economics” (Friedman, 1953) which is “the most influential work on economic methodology of the twentieth century” (Hausman 1994, p. 33), Milton Friedman states that “… the question whether a theory is realistic ‘enough’ can be settled only by seeing whether it yields predictions that are good enough for the purpose in hand or that are better than predictions from alternative theories.” The value of prediction is not repudiated by behavioral economists; in fact, different strands of behavioral economics still have elements of positivism (Tomer 2007). To illustrate, as an item on the behavioral economics agenda, Herbert Simon (1987) emphasized on “strengthen[ing] the predictions that can be made about human economic behavior.” (p. 221) In the same vein, Camerer and Loewenstein (2004) — as two well-known behavioral economists state that they “share the modernist view that the ultimate test of a theory is the accuracy with which it identifies the actual causes of behavior; making accurate predictions is a big clue that a theory has pinned down the right causes,
but more realistic assumptions are surely helpful too.” (p. 4) Consistently, Thaler (cited in Rieskamp et al. 2006) refers to the findings of Tversky and Kahneman’s program and posits that the extracted “mental illusions should be considered as the rule rather than the exception”—in which case, such systematic and predictable biases can be put to the acid test of prediction to further answer the Simon’s question (1978): “Are there important, empirically verified, aggregate predictions that follow from the theory of perfect rationality but that do not follow from behavioral theories of rationality?”

4.1. Descriptive and Predictive Datasets

Given the initial set of decision rules described in Chapter 3, we explore the B2B service database for any evidence of connection between rational and/or boundedly-rational service quality assessment and churn. We have identified a few thousand churners by manually examining their service episodes. We use one third of the churners to devise the descriptive dataset and the remaining two thirds for the predictive dataset. For confidentiality issues, we keep the ratio of churners to non-churners at 1:9 in our descriptive and 1:5 in our predictive datasets. The service episodes of non-churners in both datasets are selected based on the service episodes of the corresponding churners. To illustrate, for every churner in the descriptive dataset we randomly select nine non-churners (that have not been selected by the process yet) whose initial service episodes are longer than the churner’s. Subsequently, we select their service episodes so that:
1. The ending of the episodes coincides with the churner’s and,

2. Their episodes’ length is equal to the churner’s.

Such matched sampling is used to control for common events in time that might influence all customers. The matched sampling algorithm to build the predictive dataset (1:5) can be found in Appendix B.

The predictive analyses are conducted through ten rounds of randomly stratified subsampling within the predictive dataset—two thirds for training and one third for testing. The results’ robustness is verified through a sensitivity analysis described later.

4.2. Descriptive Analyses

We explore the descriptive dataset to investigate the applications of heuristics in SMEs’ decisions by extracting the following three measures

1. The relative percentage of churners that immediately follow the firing of a heuristic compared to non-churners,

2. The relative percentage of churners for whom the heuristic raised an alarm at least once compared to non-churners,

3. The relative average alarm frequency of a heuristic for churners compared to non-churners.
We conclude the descriptive analysis with a comparison between the actual service pain that the churners and non-churners have experienced—as a rational assessment of service quality.

### 4.2.1. Behavioral Decision Rules

To search for evidence of the application of heuristics we analyze the information extracted based on the temporal locus of a six-week sliding window. That is, for each SME, starting from the 25th week of the SME’s specific service episode we extract the measures included in all decision rules with respect to all SQIs and subsequently investigate whether the conditions for a specific decision rule hold or not. Having registered the results of the exploration for the current temporal locus of the sliding window, we move the window ahead for one week, update the relevant measures, and repeat our investigation until we reach the end of the SME’s service episode. The first twenty four weeks of the service episode are left as the initial benchmark for the extensional decision rules (e.g. DS2).

For each SQI, in addition to its relevant instant pains \( p_t \), we conduct the same analysis with instant proportional pains \( \bar{p}_t \). Furthermore, the same analysis is conducted for \( pi_t \)—which is a measure inherent to the holistic SQI and addresses the overall number of service failures in a specific week regardless of their types. To illustrate, let us suppose that in a specific week, there is one service failure of SQI1, one failure of
SQL2, and no failures of the rest of SQIs. Here, \( p_t \) is equal to 2, whereas \( \bar{p}_t \) corresponding to the holistic SQI is sum of the weights of SQL1 and SQL2 that has been suggested by a domain expert.

Table 1 addresses a comparison between the percentage of churners for whom the condition of a heuristic holds within the last six weeks prior to defection, and the same percentage for non-churners (Measure 1). We extract the percentage of non-churners for whom the condition of the relevant heuristic holds in the last six weeks of their matched service episodes. Except for three bolded statistics which concern the existence of proportional peak pain in the last six weeks prior to churn, Table 1 does not reveal any obvious applications of the suggested heuristics.

**Table 1.** Relative Importance of Decision Rules for Churners Compared to Nonchurners (Measure 1)

<table>
<thead>
<tr>
<th></th>
<th>SQL1</th>
<th>SQL2</th>
<th>SQL3</th>
<th>SQL4</th>
<th>SQL5</th>
<th>SQL6</th>
<th>SQL7</th>
<th>SQL8</th>
<th>Holistic SQI</th>
</tr>
</thead>
<tbody>
<tr>
<td>DR1</td>
<td>0.93</td>
<td>0.97</td>
<td>0.82</td>
<td>0.83</td>
<td>1.00</td>
<td>1.10</td>
<td>1.00</td>
<td>1.08</td>
<td>0.98</td>
</tr>
<tr>
<td>DR2</td>
<td>1.09</td>
<td>1.15</td>
<td>1.08</td>
<td>1.14</td>
<td>0.85</td>
<td>0.86</td>
<td>1.00</td>
<td>1.08</td>
<td>1.17</td>
</tr>
<tr>
<td>DR3</td>
<td>0.93</td>
<td>1.32</td>
<td>1.12</td>
<td>1.37</td>
<td>0.92</td>
<td>0.68</td>
<td>0.73</td>
<td>1.05</td>
<td>1.22</td>
</tr>
<tr>
<td>DR4</td>
<td>0.84</td>
<td>0.95</td>
<td>0.82</td>
<td>0.79</td>
<td>1.02</td>
<td>1.17</td>
<td>1.00</td>
<td>1.11</td>
<td>0.91</td>
</tr>
<tr>
<td>DR5</td>
<td>0.87</td>
<td>0.96</td>
<td>0.80</td>
<td>0.79</td>
<td>1.04</td>
<td>1.17</td>
<td>1.00</td>
<td>1.07</td>
<td>0.88</td>
</tr>
</tbody>
</table>

The bold statistics in Table 1 address a relatively rational manifestation of the peak pain rule as they also consider the received utility as represented in \( \bar{p}_t \). As an illustration, while the condition for the peak pain (DR3) with respect to SQL1(\( \bar{p}_t \)) holds 32% more in the last 6 weeks of churners’ service episodes than for the non-churners’, the same decision rule with respect to SQL1(\( p_t \)) has an opposite trajectory. Also, the bold statistics in this table do not necessarily attribute defection to the application of the corresponding
decision rules. Take for example the bold statistic in [DR3, $SQI_2(\bar{p}_t)$]. In this case, 10.4% of churners have experienced the corresponding peak proportional pain in their last six weeks prior to defection, while this number is 7.6% for non-churners (i.e. $\frac{10.4\%}{7.6\%} = 1.37$).

Yet, about 50% of the churners in the numerator did not follow the same decision rules more than 4 times within their service episodes. That is, the same decision rule had set off an alarm but they did not churn subsequently.

**Table 2. Relative Importance of Decision Rules for Churners Compared to Nonchurners (Measure 2)**

<table>
<thead>
<tr>
<th></th>
<th>$SQI_1$</th>
<th>$SQI_2$</th>
<th>$SQI_3$</th>
<th>$SQI_4$</th>
<th>$SQI_5$</th>
<th>$SQI_6$</th>
<th>$SQI_7$</th>
<th>$SQI_8$</th>
<th>Holistic $SQI$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$p_t$</td>
<td>$\bar{p}_t$</td>
<td>$p_t$</td>
<td>$\bar{p}_t$</td>
<td>$p_t$</td>
<td>$\bar{p}_t$</td>
<td>$p_t$</td>
<td>$\bar{p}_t$</td>
<td>$p_t$</td>
</tr>
<tr>
<td>DR1</td>
<td>1.00</td>
<td>1.02</td>
<td>0.96</td>
<td>0.98</td>
<td>1.07</td>
<td>1.20</td>
<td>1.22</td>
<td>1.06</td>
<td>1.01</td>
</tr>
<tr>
<td>DR2</td>
<td>1.01</td>
<td>1.02</td>
<td>1.20</td>
<td>1.29</td>
<td>0.96</td>
<td>0.96</td>
<td>0.98</td>
<td>1.07</td>
<td>1.21</td>
</tr>
<tr>
<td>DR3</td>
<td>0.93</td>
<td>1.00</td>
<td>1.04</td>
<td>1.09</td>
<td>0.96</td>
<td>1.01</td>
<td>0.97</td>
<td>1.00</td>
<td>1.08</td>
</tr>
<tr>
<td>DR4</td>
<td>0.98</td>
<td>1.02</td>
<td>0.96</td>
<td>0.98</td>
<td>1.06</td>
<td>1.21</td>
<td>1.23</td>
<td>1.06</td>
<td>1.05</td>
</tr>
<tr>
<td>DR5</td>
<td>0.99</td>
<td>1.02</td>
<td>0.96</td>
<td>0.99</td>
<td>1.07</td>
<td>1.21</td>
<td>1.23</td>
<td>1.06</td>
<td>1.00</td>
</tr>
</tbody>
</table>

To alleviate the inaccuracy inherent to the timing of defection, we extract two measures that highlight the relative importance of heuristics application with respect to the entire service episode, and not just its end. In this sense, each cell’s statistic in Table 2 addresses a comparison between the percentage of churners for whom the condition of the relevant decision rule holds at least once in their service episode and the same percentage for non-churners (Measure 2). This statistic is intended to alleviate the inaccuracy inherent to the timing of defection by including the cases where an organization acted upon an alarm, but with some delay. Note that in most cases, this statistic is equal to one or slightly above it; i.e. the percentage of churners and non-churners that could pick up the signals of a decision rule at least once is not practically
different. There are even cases where an alarm is stronger for non-churners but they disregard it. There is only one bolded case ([DR3, \( SQI_8(p_t) \)]) for which the difference is close to 50%.

**Table 3.** Relative Importance of Decision Rules for Churners Compared to Nonchurners (Measure 3)

<table>
<thead>
<tr>
<th>( SQI_1 )</th>
<th>( SQI_2 )</th>
<th>( SQI_3 )</th>
<th>( SQI_4 )</th>
<th>( SQI_5 )</th>
<th>( SQI_6 )</th>
<th>( SQI_7 )</th>
<th>( SQI_8 )</th>
<th>Holistic SQI</th>
</tr>
</thead>
<tbody>
<tr>
<td>( p_t )</td>
<td>( \bar{p}_t )</td>
<td>( p_t )</td>
<td>( \bar{p}_t )</td>
<td>( p_t )</td>
<td>( \bar{p}_t )</td>
<td>( p_t )</td>
<td>( \bar{p}_t )</td>
<td>( p_t )</td>
</tr>
<tr>
<td>DR1</td>
<td>0.97</td>
<td>1.00</td>
<td>0.95</td>
<td>1.03</td>
<td>1.10</td>
<td>1.20</td>
<td>\textbf{1.30}</td>
<td>\textbf{1.30}</td>
</tr>
<tr>
<td>DR2</td>
<td>0.00</td>
<td>1.04</td>
<td>1.00</td>
<td>1.00</td>
<td>0.95</td>
<td>0.99</td>
<td>1.00</td>
<td>1.20</td>
</tr>
<tr>
<td>DR3</td>
<td>0.94</td>
<td>1.06</td>
<td>1.10</td>
<td>1.05</td>
<td>0.95</td>
<td>0.99</td>
<td>0.93</td>
<td>1.10</td>
</tr>
<tr>
<td>DR4</td>
<td>0.94</td>
<td>1.00</td>
<td>0.92</td>
<td>0.99</td>
<td>1.10</td>
<td>1.19</td>
<td>\textbf{1.31}</td>
<td>1.03</td>
</tr>
<tr>
<td>DR5</td>
<td>0.94</td>
<td>1.00</td>
<td>0.94</td>
<td>1.00</td>
<td>1.11</td>
<td>1.19</td>
<td>\textbf{1.31}</td>
<td>1.03</td>
</tr>
</tbody>
</table>

Table 3 provides a similar comparison between the average number of times that the condition of a heuristic holds in the service episode of a churner and that average for non-churners; it indicates whether a specific alarm was set off more for churners than for non-churners (Measure 3). Again, the results show that the conditions were almost the same for churners and non-churners except for some decision rules in \( SQI_7 \).

It is noteworthy that projecting each cell of the tables in this section involves significant dynamic SQL coding. The following pseudo code illustrates an abstract of what has been done with dynamic SQL.
For each SME,
  Fetch the SME’s service episode; i.e. \([w_{\text{start}}, w_{\text{end}}]\),
  Set \([w_{\text{start}}, w_{\text{start}+23}]\) as the base,
  For each \(w_i\) in \([w_{\text{start}+24}, w_{\text{end}-5}]\),
    For each decision rule \(DR_j\),
      For each \(SQI_k\),
        Check to see if the conditions of \(DR_j\) with \(SQI_k\) \((p_t)\) holds within \([w_i, w_{i+5}]\),
        Check to see if the conditions of \(DR_j\) with \(SQI_k\)(\(\bar{p}_t\)) holds within \([w_i, w_{i+5}]\),
      Endfor,
    Endfor,
  Endfor,
Endfor,

To illustrate the scope of the ETL, note that in the above pseudo code, there are four loops; 100,000 SMEs, each with nearly 100 weeks, five different decision rules, and nine different SQIs (including the holistic one). Appendix C includes the ETL that is part of projecting the statistics corresponding to \(SQI_1\).

### 4.2.2. Rational Decision Rules

Given that the service episodes in the analysis are of different lengths, we pick the temporal average of proportional service pain \((\sigma)\) as a normative measure of actual experienced service pain/utility. That is:

\[
\sigma = \frac{\sum_{t=1}^{T} p_t}{T}.
\]
Table 4 shows that without exception and for all SQIs, the mean of $\sigma$ for churners is greater than the one for non-churners—suggesting that churners have actually been subjected to more total service pain than non-churners. This suggests lower actual service quality for churners throughout their past episodes of business interaction. To illustrate, let us consider the column denoted by $SQI_1$: for a typical nonchurner, in every week on average, 1.49% of the service units suffered from the pain relevant to $SQI_1$, whereas this ratio is 1.65% for churners. (A reminder that the holistic percentages are large due to the weights for each SQI as assigned by the industry expert that are factored into the average.)

**Table 4. Temporal Average of Proportional Service Pain**

<table>
<thead>
<tr>
<th></th>
<th>$SQI_1$</th>
<th>$SQI_2$</th>
<th>$SQI_3$</th>
<th>$SQI_4$</th>
<th>$SQI_5$</th>
<th>$SQI_6$</th>
<th>$Holistic\ SQI$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Non-churners</strong></td>
<td>1.49%</td>
<td>0.50%</td>
<td>0.16%</td>
<td>0.83%</td>
<td>0.06%</td>
<td>0.50%</td>
<td>0.013%</td>
</tr>
<tr>
<td><strong>Churners</strong></td>
<td>1.65%</td>
<td>0.61%</td>
<td>0.19%</td>
<td>0.84%</td>
<td>0.07%</td>
<td>0.59%</td>
<td>0.017%</td>
</tr>
</tbody>
</table>

Given that the statistics in Table 4 correspond to the normative models of decision making in mainstream economics, we do apply tests of statistical significance. To investigate whether the mean of $\sigma$ is significantly greater for churners than for non-churners, we conduct Analyses of Variance (ANOVA) on $\sigma$ with regard to each SQI. We first conduct an omnibus MANOVA. At any level of $\alpha$, it is determined that significant differences exist between the two groups since Wilk’s Lambda, Pillai’s Trace, Hotelling-Lawley Trace, and Roy’s Greatest Root report $p$-values less than 0.0001. Although the utility and the duration of service episodes are both embedded in $\sigma$, we still include them...
as the covariances in our analyses. Regarding the relevant assumptions, ANCOVA is robust with respect to the normality assumption for large samples. However, since we do not have a balanced design, we conduct the Levene’s test to verify the homogeneity of variances of $\sigma$ for churners and non-churners. Except for the first two SQIs, the Levene’s null hypothesis is not rejected at $\alpha$ equal to 0.01 — satisfying the corresponding assumption for seven SQIs. Among these SQIs, only the service failures related to $SQL_4$ and $SQL_7$ do not cause more significant pain for churners; i.e. the difference is highly significant for the rest of SQIs.

4.3. Predictive Analyses

Drawing from the insights gained from the description analyses of the services database, we now investigate the predictive accuracy of utility and heuristic models. (Katsikopoulos & Gigerenzer 2013; Simon 1979) We wish to demonstrate how B2B service organizations can leverage large transactional BI databases to gain customer insights (e.g. how customers perceive service quality) and subsequently use these insights to lower churn in B2B non-contractual settings. For the predictive analyses, we apply techniques from logistic regression, as it has been shown to be the most widely used and effective churn detection technique among both practitioners and academics. (Neslin et al. 2006; Lemmens & Gupta 2013) In addition to predictive accuracy, logistic regression
determines the role of different service quality assessment measures in alleviating the model’s lack of fit, besides the direction of their effect on the odds of churn.

Moreover, the statistical significances delivered by logistic regression could address a positivist perspective to this dissertation; i.e. checking if the corresponding rational/ boundedly rational pain evaluation hypotheses would survive falsification. Nonetheless, even “viewed as a body of substantive hypotheses, theory is to be judged by its predictive power for the class of phenomena which it is intended to “explain.” Only factual evidence can show whether it is “right” or “wrong” or, better, tentatively “accepted” as valid or “rejected.” As I shall argue at greater length below, the only relevant test of the validity of a hypothesis is comparison of its predictions with experience.” (Friedman 1953, p.8)

We supplement our analysis with decision trees as the second most common technique for churn detection (Neslin et al. 2006) to graphically depict the effect of service pain on defection. Lastly, we conduct a sensitivity analysis to examine the robustness of the findings.

We use the remaining two-thirds of the SME population and their service episodes to devise the predictive dataset (see Section 4.1). In summary, each observation in the dataset is comprised of an SME ID, four control variables, nine rational variables \((R_j:1\rightarrow9)\) corresponding to the nine SQIs in Table 4, twenty nine potential heuristic variables \((H_j:1\rightarrow29)\) corresponding to the heuristic decision rules (described in Table 6 and explained
further below), and a churn label (0: Loyal or 1: Churned) which represents the SME’s observed behavior on defection (Section 2.2). For each SME, the rational and heuristic variables are naturally extracted based on its specific service episode as explained in Section 2.2.

Table 5. Observation Fields in the Predictive Dataset

<table>
<thead>
<tr>
<th>SME_ID</th>
<th>Churn (0/1)</th>
<th>Control Variables</th>
<th>Rational Service Pain Assessment Variables</th>
<th>Boundedly-Rational (Heuristic) Service Pain Assessment Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Age, C₁, C₂, C₃</td>
<td>R₁, ..., R₉</td>
<td>H₁, ..., H₂₆</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Based on the SME’s whole service episode.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Rⱼ: Temporal average (σ) of service pain/utility for SQIⱼ</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Based on the SME’s whole service episode.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>See Table 6.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Based on the last six weeks of the SME’s service episode.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>See Table 6.</td>
</tr>
</tbody>
</table>

The control variables are, Age (i.e. age of SME’s relationship with the service company), C₁ (i.e. industry segment), and C₂ and C₃ that are proprietary to the service company. The first twenty six potential heuristic variables (i.e. Hⱼ:1→26) are in Table 2, since it includes more potentially significant statistics. We mainly focus on the heuristic decision rules whose conditions were satisfied 20% or more for churners than for non-churners; in which case, all such potentially important rules in Table 3 are also covered by Table 2. If a specific heuristic and SQI have two statistics (i.e. one for \( p_t \) and one for \( \tilde{p}_t \)) both exceeding 1.2, we select the greater one as the representative; except for [DR3, SQI₈] for which we suggest two potential variables as they are the only ones greater than 1.3. For each of these cells in Table 2, we suggest two potential variables, the former represents the number of times where the conditions for the relevant decision rule held.
in the past episode (i.e. measure 2 in Table 3; denoted by an odd number, e.g. \( H_1 \)), and the latter represents a binary flag showing whether the condition held at least once in the selected episode (i.e. measure 1 in Table 2; denoted by an even number, e.g. \( H_2 \)). The last three decision rules (i.e. \( H_{27}, H_{28}, \) and \( H_{29} \)) are binary flags that address the highlighted cells in Table 1 with statistics greater than 1.2. To illustrate, \( H_{27} \) is equal to one if the last proportional pain related to \( SQI_1 \) (i.e. \( SQI_1 \) end pain) has not been experienced before (i.e. peak pain decision rule holds).

Table 6. Candidates for Heuristic Decision Rule Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Heuristic Decision Rule</th>
</tr>
</thead>
<tbody>
<tr>
<td>( H_1 )</td>
<td>Number of times that the availability heuristic (incidental frequency) holds with respect to ( SQI_6 ).</td>
</tr>
<tr>
<td>( H_2 )</td>
<td>Has the condition for the availability heuristic (incidental frequency) held with respect to ( SQI_6 ) at least once?</td>
</tr>
<tr>
<td>( H_3 )</td>
<td>Number of times that the availability heuristic (temporal frequency) holds with respect to ( SQI_6 ).</td>
</tr>
<tr>
<td>( H_4 )</td>
<td>Has the condition for the availability heuristic (temporal frequency) held with respect to ( SQI_6 ) at least once?</td>
</tr>
<tr>
<td>( H_5 )</td>
<td>Number of times that the availability heuristic (incidental frequency) holds with respect to ( SQI_7 ).</td>
</tr>
<tr>
<td>( H_6 )</td>
<td>Has the condition for the availability heuristic (incidental frequency) held with respect to ( SQI_7 ) at least once?</td>
</tr>
<tr>
<td>( H_7 )</td>
<td>Number of times that the availability heuristic (temporal frequency) holds with respect to ( SQI_7 ).</td>
</tr>
<tr>
<td>( H_8 )</td>
<td>Has the condition for the availability heuristic (temporal frequency) held with respect to ( SQI_7 ) at least once?</td>
</tr>
<tr>
<td>( H_9 )</td>
<td>Number of times that the end pain heuristic holds with respect to ( SQI_6 ).</td>
</tr>
<tr>
<td>( H_{10} )</td>
<td>Has the condition for the end pain heuristic held with respect to ( SQI_6 ) at least once?</td>
</tr>
<tr>
<td>( H_{11} )</td>
<td>Number of times that the end pain heuristic holds with respect to ( SQI_7 ).</td>
</tr>
<tr>
<td>( H_{12} )</td>
<td>Has the condition for the end pain heuristic held with respect to ( SQI_7 ) at least once?</td>
</tr>
<tr>
<td>( H_{13} )</td>
<td>Number of times that the extensional end pain heuristic (with ( \bar{p}_t )) holds with respect to ( SQI_2 ).</td>
</tr>
<tr>
<td>( H_{14} )</td>
<td>Has the condition for the extensional end pain heuristic (with ( \bar{p}_t )) held with respect to ( SQI_2 ) at least once?</td>
</tr>
<tr>
<td>( H_{15} )</td>
<td>Number of times that the extensional end pain heuristic (with ( \bar{p}_t )) holds with respect to ( SQI_6 ).</td>
</tr>
<tr>
<td>( H_{16} )</td>
<td>Has the condition for the extensional end pain heuristic (with ( \bar{p}_t )) held with respect to ( SQI_6 ) at least once?</td>
</tr>
<tr>
<td>( H_{17} )</td>
<td>Number of times that the extensional end pain heuristic (with ( \bar{p}_t )) holds with respect to ( SQI_7 ).</td>
</tr>
<tr>
<td>( H_{18} )</td>
<td>Has the condition for the extensional end pain heuristic (with ( \bar{p}_t )) held with respect to ( SQI_7 ) at least once?</td>
</tr>
<tr>
<td>( H_{19} )</td>
<td>Number of times that the peak pain heuristic (with ( \bar{p}_t )) holds with respect to ( SQI_6 ).</td>
</tr>
<tr>
<td>( H_{20} )</td>
<td>Has the condition for the peak pain heuristic (with ( \bar{p}_t )) held with respect to ( SQI_6 ) at least once?</td>
</tr>
<tr>
<td>( H_{21} )</td>
<td>Number of times that the peak pain heuristic (with ( \bar{p}_t )) holds with respect to ( SQI_7 ).</td>
</tr>
<tr>
<td>( H_{22} )</td>
<td>Has the condition for the peak pain heuristic (with ( \bar{p}_t )) held with respect to ( SQI_7 ) at least once?</td>
</tr>
<tr>
<td>( H_{23} )</td>
<td>Number of times that the peak pain heuristic (with ( \bar{p}_t )) holds with respect to ( SQI_8 ).</td>
</tr>
<tr>
<td>( H_{24} )</td>
<td>Has the condition for the peak pain heuristic (with ( \bar{p}_t )) held with respect to ( SQI_8 ) at least once?</td>
</tr>
<tr>
<td>( H_{25} )</td>
<td>Number of times that the peak pain heuristic (with ( \bar{p}_t )) holds with respect to ( SQI_8 ).</td>
</tr>
<tr>
<td>( H_{26} )</td>
<td>Has the condition for the peak pain heuristic (with ( \bar{p}_t )) held with respect to ( SQI_8 ) at least once?</td>
</tr>
<tr>
<td>( H_{27} )</td>
<td>Has the condition for the peak pain heuristic (with ( \bar{p}_t )) held with respect to ( SQI_1 ) at the end of the episode?</td>
</tr>
<tr>
<td>( H_{28} )</td>
<td>Has the condition for the peak pain heuristic (with ( \bar{p}_t )) held with respect to ( SQI_2 ) at the end of the episode?</td>
</tr>
<tr>
<td>( H_{29} )</td>
<td>Has the condition for the peak pain heuristic (with ( \bar{p}_t )) held with respect to ( SQI_5 ) at the end of the episode?</td>
</tr>
</tbody>
</table>
It is important to note that $H_{27}$, $H_{28}$, and $H_{29}$ are extracted based on the last six weeks of the SME’s service episode, which makes them deserve more attention from the behavioral economics perspective compared to the first twenty six suggested variables for heuristic rules. This is mainly due to the “snapshot model” (Fredrickson and Kahneman 1993) that explains the retrospective evaluations of the past episodes; i.e. human beings evaluate their past episodes of experience by constructing a *representative moment* and subsequently evaluating the utility of that moment (Kahneman et al. 2003).

As a result, the temporal dimension of the organizational service experience is neglected (Kahneman 2000) whereas there is a focus on the *recency* aspect of the snapshot. Yet, the first twenty six suggested variables coming from Tables 2 and 3 incorporate the temporal dimension since they are computed based on the whole episode. On the other hand, $H_{27}$, $H_{28}$, and $H_{29}$ are extracted based on the last six weeks of the SME’s service episode; which in case of the churners are based on the last six weeks before the churn. As a reminder, the Table 2 and Table 3 have been extracted partly to alleviate any potential inaccuracy inherent to the timing of defection.

In the same vein, among the first twenty six potential variables for heuristic decision rules, a potential variable with an odd index could be correlated with the corresponding variable with the even index. That is, when the number of times that conditions for a decision rule hold is greater than zero, the corresponding flag is one.
This, however, does not apply to $H_{27}, H_{28}$ and $H_{29}$ which are extracted based on the last six weeks of the service episodes.

Thus we refrain from selecting predictor variables using stepwise methods considering their perils in logistic regression. (Shtatland et al. 2005) This observation deserves subtler attention considering the pervasiveness of stepwise methods in the churn analytics community (Neslin et al. 2006). To avoid over-fitting due to multicollinearity and as an initial filter for predictor variables, in every round we employ the tolerance value of 0.1 as the cutoff threshold. Tolerance is defined as “the amount of variability of the selected independent variable not explained by the other independent variables” (Hair et al. 2010) All the first eight rational variables are highly tolerant in all rounds; i.e. tolerance values are mostly in the ranges of 0.9 and 0.7. (Note that $R_9$ is the holistic SQI’s $\sigma$; i.e. a linear combination of eight individual SQIs, which we expect not to be tolerant.)

Among the heuristic variables, $H_{27}, H_{28}$ and $H_{29}$ which are extracted based on the last six weeks of the service episodes, are highly tolerant throughout all ten rounds, i.e. tolerance values are greater than 0.9. Among the rest of the potential variables for heuristic decision rules that are computed based on the SME’s whole service episode, only $H_{13}$ is moderately tolerant and the rest are highly intolerant.

In addition to the predictor variables that pass the tolerance filter, we include three interaction terms between $H_{27}, H_{28}, H_{29}$ and their corresponding rational assessment
variables—in accordance with the hypothesized role of heuristics as “attentional mechanisms” (see Section 3.3). To illustrate, since $H_{27}$ addresses the existence of the peak proportional $SQI_1$ pain in the last six weeks of the episode, we include $H_{27} \times R_1$ in the model. That is, we posit that the existence of peak pain (i.e. $H_{27}=1$) can realize/exacerbate the effect of the rational assessment of the relevant pain (i.e. $R_1$) on the odds of defection.

Table 7 summarizes the statistically significant predictor variables, their significance level, and their effect direction on the odds of churn throughout the ten rounds of random stratified subsampling. The table shows that throughout the random subsampling, SME’s age of business relationship with the service company stays highly significant with a negative effect on the odds of defection from the company. Holding other variables fixed, the odds of defection decreases by approximately -3.7% as the relationship ages for one year. It is noteworthy that the average relationship age is significantly less for churners than for non-churners; churners’ average relationship age is less than ten whereas the non-churners’ is greater than twelve years. This addresses the importance of a well-established inter-organizational relationship in B2B service operations management.

Regarding the relationship between the SME-perceived service quality and B2B loyalty, both rational and boundedly-rational assessments of increased service pain are found to consistently increase the odds of defection. To illustrate, holding other variables fixed, one percent of increase in the temporal average of $SQI_1$ proportional pain will
increase the odds of defection by 7.25%. Moreover, the existence of service peak pain is shown to either realize or exacerbate the effect of the rational pain assessment on churn (e.g. $H_{29} * R_5$ and $H_{27} * R_1$ respectively). That is, peak pain can cause a somatic state in SMEs— calling for a decision on loyalty that can be made using the rational measures of service quality assessment.

Table 7. Statistically Significant Models

<table>
<thead>
<tr>
<th>Control Variables</th>
<th>Rational Service Pain Assessment Variables</th>
<th>Boundedly-Rational Service Pain Assessment Variables</th>
<th>Somatic Marker Hypothesis</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$-\text{Age}^{<em><strong>}, C_1^{</strong></em>}, C_3^{***}$</td>
<td>$+R_1^{<em><strong>}, +R_3^{</strong></em>}, +R_5^{***}$</td>
<td>$+H_{13}^{***}$</td>
</tr>
<tr>
<td>2</td>
<td>$-\text{Age}^{<em><strong>}, C_1^{</strong></em>}, C_3^{***}$</td>
<td>$+R_1^{<em><strong>}, +R_3^{</strong></em>}, +R_5^{***}$</td>
<td>$+H_{13}^{***}$</td>
</tr>
<tr>
<td>3</td>
<td>$-\text{Age}^{<em><strong>}, C_1^{</strong></em>}, C_3^{***}$</td>
<td>$+R_1^{<em><strong>}, +R_3^{</strong></em>}, +R_5^{***}$</td>
<td>$+H_{13}^{***}$</td>
</tr>
<tr>
<td>4</td>
<td>$-\text{Age}^{<em><strong>}, C_1^{</strong></em>}, C_3^{***}$</td>
<td>$+R_1^{<em><strong>}, +R_3^{</strong></em>}, +R_5^{***}$</td>
<td>$+H_{13}^{***}$</td>
</tr>
<tr>
<td>5</td>
<td>$-\text{Age}^{<em><strong>}, C_1^{</strong></em>}, C_3^{***}$</td>
<td>$+R_1^{<em><strong>}, +R_3^{</strong></em>}, +R_5^{***}$</td>
<td>$+H_{13}^{***}$</td>
</tr>
<tr>
<td>6</td>
<td>$-\text{Age}^{<em><strong>}, C_1^{</strong></em>}, C_3^{***}$</td>
<td>$+R_1^{<em><strong>}, +R_3^{</strong></em>}, +R_5^{***}$</td>
<td>$+H_{13}^{***}$</td>
</tr>
<tr>
<td>7</td>
<td>$-\text{Age}^{<em><strong>}, C_1^{</strong></em>}, C_3^{***}$</td>
<td>$+R_1^{<em><strong>}, +R_3^{</strong></em>}, +R_5^{***}$</td>
<td>$+H_{13}^{***}$</td>
</tr>
<tr>
<td>8</td>
<td>$-\text{Age}^{<em><strong>}, C_1^{</strong></em>}, C_3^{***}$</td>
<td>$+R_1^{<em><strong>}, +R_3^{</strong></em>}, +R_5^{***}$</td>
<td>$+H_{13}^{***}$</td>
</tr>
<tr>
<td>9</td>
<td>$-\text{Age}^{<em><strong>}, C_1^{</strong></em>}, C_3^{***}$</td>
<td>$+R_1^{<em><strong>}, +R_3^{</strong></em>}, +R_5^{***}$</td>
<td>$+H_{13}^{***}$</td>
</tr>
<tr>
<td>10</td>
<td>$-\text{Age}^{<em><strong>}, C_1^{</strong></em>}, C_3^{***}$</td>
<td>$+R_1^{<em><strong>}, +R_3^{</strong></em>}, +R_5^{***}$</td>
<td>$+H_{13}^{***}$</td>
</tr>
</tbody>
</table>

***Significant at $\alpha=0.001$, **Significant at $\alpha=0.01$, *Significant at $\alpha=0.05$. Significance of the coefficients is based on Wald $\chi^2$ tests.

The highlighted role of somatic states in organizational decision-making indicates that the corresponding decision rules deserve more attention. These decision rules are suggested based on the representativeness and availability heuristics as the main focus of the Heuristics and Biases research program. (Kahneman & Frederick 2002) Although an extensive list of norm violations can be explained in terms of these heuristics (Tversky & Kahneman 1974), they might have different materializations as decision rules in the context of B2B service operations management. To illustrate, the peak pain decision rule in this dissertation is implemented with ‘$>$’ operator; it holds when the current pain is greater than any pain experienced before. Figure 7.a plots the number of churners against
the timing of the somatic state caused by this decision rule with respect to $SQI_2$. The plot suggests that the somatic state caused by the proportional peak pain related to $SQI_2$ has a significant effect within 29 weeks. Yet, the same decision rule highlights a more striking pattern (Figure 7.b) if it is implemented with ‘≽’ operator (greater than or equal to), which corroborates Construal Level Theory (Trope & Liberman 2003) according to which people may find distal objects and events more abstract than proximal ones. Such discriminations in the implementation of decision rules are captured by virtue of mining the large granular database.

![Figure 7](image)

**Figure 7.** Distribution of Churners and Timings of the Peak Pain with (a) ‘≽’ and (b) ‘≽’

### 4.3.1. Sensitivity Analysis

The use of expert opinion as part of the churn detection process calls for verification of the results’ robustness with respect to the labeled churners. We conduct a sensitivity analysis by continuously removing 5% of random churners from a training
stratum and investigating the change in the predictor variables significance. Table 8 shows the results of the sensitivity analysis. While $R_1$ loses its significance following the removal of the 35% of churners, all other variables carry their significance until the removal of 50% of the labeled churners form the training stratum — highlighting the robustness of our results against the only human element in this dissertation.

**Table 8. Sensitivity Analysis**

<table>
<thead>
<tr>
<th>Control Variables</th>
<th>Rational Service Pain Assessment Variables</th>
<th>Boundedly Rational Service Pain Assessment Variables</th>
<th>Somatic Marker Hypothesis</th>
</tr>
</thead>
<tbody>
<tr>
<td>-5%</td>
<td>$-Age^{<em><strong>}, C_1^{</strong></em>}, C_2^{<em><strong>}$ +$R_1^{</strong></em>}$ +$R_2^{<em><strong>}$ ++$R_6^{</strong></em>}$ +$R_8^{***}$</td>
<td>+$H_{13}^{<em><strong>}$ +$H_{27}^{</strong></em>}$ +$H_{28}^{<em><strong>}$ +$R_2^{</strong></em>}$ +$H_{29}^{***}$</td>
<td></td>
</tr>
<tr>
<td>-10%</td>
<td>$-Age^{<em><strong>}, C_1^{</strong></em>}, C_2^{<em><strong>}$ +$R_1^{</strong></em>}$ +$R_2^{<em><strong>}$ +$R_6^{</strong></em>}$ +$R_8^{***}$</td>
<td>+$H_{13}^{<em><strong>}$ +$H_{27}^{</strong></em>}$ +$H_{28}^{<em><strong>}$ +$R_2^{</strong></em>}$ +$H_{29}^{***}$</td>
<td></td>
</tr>
<tr>
<td>-15%</td>
<td>$-Age^{<em><strong>}, C_1^{</strong></em>}, C_2^{<em><strong>}$ +$R_1^{</strong></em>}$ +$R_2^{<em><strong>}$ +$R_6^{</strong></em>}$ +$R_8^{***}$</td>
<td>+$H_{13}^{<em><strong>}$ +$H_{27}^{</strong></em>}$ +$H_{28}^{<em><strong>}$ +$R_2^{</strong></em>}$ +$H_{29}^{***}$</td>
<td></td>
</tr>
<tr>
<td>-20%</td>
<td>$-Age^{<em><strong>}, C_1^{</strong></em>}, C_2^{<em><strong>}$ +$R_1^{</strong></em>}$ +$R_2^{<em><strong>}$ +$R_6^{</strong></em>}$ +$R_8^{***}$</td>
<td>+$H_{13}^{<em><strong>}$ +$H_{27}^{</strong></em>}$ +$H_{28}^{<em><strong>}$ +$R_2^{</strong></em>}$ +$H_{29}^{***}$</td>
<td></td>
</tr>
<tr>
<td>-25%</td>
<td>$-Age^{<em><strong>}, C_1^{</strong></em>}, C_2^{<em><strong>}$ +$R_1^{</strong></em>}$ +$R_2^{<em><strong>}$ +$R_6^{</strong></em>}$ +$R_8^{***}$</td>
<td>+$H_{13}^{<em><strong>}$ +$H_{27}^{</strong></em>}$ +$H_{28}^{<em><strong>}$ +$R_2^{</strong></em>}$ +$H_{29}^{***}$</td>
<td></td>
</tr>
<tr>
<td>-30%</td>
<td>$-Age^{<em><strong>}, C_1^{</strong></em>}, C_2^{<em><strong>}$ +$R_1^{</strong></em>}$ +$R_2^{<em><strong>}$ +$R_6^{</strong></em>}$ +$R_8^{***}$</td>
<td>+$H_{13}^{<em><strong>}$ +$H_{27}^{</strong></em>}$ +$H_{28}^{<em><strong>}$ +$R_2^{</strong></em>}$ +$H_{29}^{***}$</td>
<td></td>
</tr>
<tr>
<td>-35%</td>
<td>$-Age^{<em><strong>}, C_1^{</strong></em>}, C_2^{<em><strong>}$ +$R_1^{</strong></em>}$ +$R_2^{<em><strong>}$ +$R_6^{</strong></em>}$ +$R_8^{***}$</td>
<td>+$H_{13}^{<em><strong>}$ +$H_{27}^{</strong></em>}$ +$H_{28}^{<em><strong>}$ +$R_2^{</strong></em>}$ +$H_{29}^{***}$</td>
<td></td>
</tr>
<tr>
<td>-40%</td>
<td>$-Age^{<em><strong>}, C_1^{</strong></em>}, C_2^{<em><strong>}$ +$R_1^{</strong></em>}$ +$R_2^{<em><strong>}$ +$R_6^{</strong></em>}$ +$R_8^{***}$</td>
<td>+$H_{13}^{<em><strong>}$ +$H_{27}^{</strong></em>}$ +$H_{28}^{<em><strong>}$ +$R_2^{</strong></em>}$ +$H_{29}^{***}$</td>
<td></td>
</tr>
<tr>
<td>-45%</td>
<td>$-Age^{<em><strong>}, C_1^{</strong></em>}, C_2^{<em><strong>}$ +$R_1^{</strong></em>}$ +$R_2^{<em><strong>}$ +$R_6^{</strong></em>}$ +$R_8^{***}$</td>
<td>+$H_{13}^{<em><strong>}$ +$H_{27}^{</strong></em>}$ +$H_{28}^{<em><strong>}$ +$R_2^{</strong></em>}$ +$H_{29}^{***}$</td>
<td></td>
</tr>
<tr>
<td>-50%</td>
<td>$-Age^{<em><strong>}, C_1^{</strong></em>}, C_2^{<em><strong>}$ +$R_1^{</strong></em>}$ +$R_2^{<em><strong>}$ +$R_6^{</strong></em>}$ +$R_8^{***}$</td>
<td>+$H_{13}^{<em><strong>}$ +$H_{27}^{</strong></em>}$ +$H_{28}^{<em><strong>}$ +$R_2^{</strong></em>}$ +$H_{29}^{***}$</td>
<td></td>
</tr>
</tbody>
</table>

***Significant at $\alpha=0.001$, **Significant at $\alpha=0.01$, *Significant at $\alpha=0.05$. Significance of the coefficients is based on Wald $\chi^2$ tests.

### 4.3.2. Predictive Accuracy

In this section, we let the logit models estimate the odds of SMEs defection in the corresponding testing stratum. In addition to the logit models in Table 7, in each round we extract a decision tree using the corresponding training stratum. We subsequently benchmark the predicted outcomes of logit models and decision trees against the churn flag and plot the corresponding Receiver Operating Characteristic (ROC) curves. ROC curves basically address the tradeoff between the model’s true positive rate (sensitivity) and false positive rate (1-specificity) at different thresholds. Research has shown that the Area Under the ROC Curve (AUC) stands out from the rest of evaluation measures
including misclassification rate (Culver et al. 2006), especially in cases of unbalanced datasets. Such measures of practical significance are especially important since they benchmark the models’ predictions against the observed behavior.

Table 9. Area under the ROC Curves

<table>
<thead>
<tr>
<th>Control and Rational</th>
<th>Logit</th>
<th>Tree</th>
<th>Logit</th>
<th>Tree</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>Logit</td>
<td>Tree</td>
<td>Logit</td>
<td>Tree</td>
</tr>
<tr>
<td>1</td>
<td>0.6563</td>
<td>0.630</td>
<td>0.6496</td>
<td>0.619</td>
</tr>
<tr>
<td>2</td>
<td>0.6542</td>
<td>0.639</td>
<td>0.6469</td>
<td>0.623</td>
</tr>
<tr>
<td>3</td>
<td>0.6524</td>
<td>0.630</td>
<td>0.6394</td>
<td>0.637</td>
</tr>
<tr>
<td>4</td>
<td>0.6504</td>
<td>0.625</td>
<td>0.6389</td>
<td>0.609</td>
</tr>
<tr>
<td>5</td>
<td>0.6431</td>
<td>0.623</td>
<td>0.6384</td>
<td>0.621</td>
</tr>
<tr>
<td>6</td>
<td>0.6574</td>
<td>0.633</td>
<td>0.6448</td>
<td>0.631</td>
</tr>
<tr>
<td>7</td>
<td>0.6568</td>
<td>0.635</td>
<td>0.6458</td>
<td>0.616</td>
</tr>
<tr>
<td>8</td>
<td>0.6639</td>
<td>0.633</td>
<td>0.6499</td>
<td>0.616</td>
</tr>
<tr>
<td>9</td>
<td>0.6586</td>
<td>0.637</td>
<td>0.6509</td>
<td>0.634</td>
</tr>
<tr>
<td>10</td>
<td>0.6591</td>
<td>0.622</td>
<td>0.6436</td>
<td>0.632</td>
</tr>
<tr>
<td>Avg</td>
<td>0.6551</td>
<td>0.6307</td>
<td>0.64482</td>
<td>0.6238</td>
</tr>
</tbody>
</table>

In addition to the AUC of complete models, we extract the AUCs of three sets of predictor variables in the models separately (i.e. controls, controls and rational, rational and boundedly-rational) to investigate their contribution to the predictive accuracy. It should be noted that unlike the logit models, we leave all twenty nine heuristic variables in the decision tree building process. Table 9 indicates that the controls are the principal variables in terms of predictive accuracy. That is, the models’ predictive accuracy is practically achieved by virtue of the control variables; the models with merely service quality variables only yield the AUC of 0.55. This can be explained by the fact that the service quality variables are extracted using two years of data, whereas the average
relationship age of SMEs with the company is eleven years. That is, we are trying to predict the behavior of the SMEs that have had a long-term relationship with the company using only two years of service intelligence.

Table 10. AUC for Relationship Age less than Two Years

<table>
<thead>
<tr>
<th></th>
<th>Complete Model</th>
<th>Control</th>
<th>Control and Rational</th>
<th>Rational and Boundedly Rational</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.5690</td>
<td>0.5257</td>
<td>0.5563</td>
<td>0.587</td>
</tr>
<tr>
<td>2</td>
<td>0.6286</td>
<td>0.5688</td>
<td>0.6056</td>
<td>0.6138</td>
</tr>
<tr>
<td>3</td>
<td>0.6212</td>
<td>0.5531</td>
<td>0.6184</td>
<td>0.5854</td>
</tr>
<tr>
<td>4</td>
<td>0.6294</td>
<td>0.5902</td>
<td>0.5878</td>
<td>0.5814</td>
</tr>
<tr>
<td>5</td>
<td>0.6101</td>
<td>0.5294</td>
<td>0.5713</td>
<td>0.6264</td>
</tr>
<tr>
<td>6</td>
<td>0.6348</td>
<td>0.5033</td>
<td>0.5890</td>
<td>0.6728</td>
</tr>
<tr>
<td>7</td>
<td>0.6537</td>
<td>0.5611</td>
<td>0.6244</td>
<td>0.6442</td>
</tr>
<tr>
<td>8</td>
<td>0.5912</td>
<td>0.5164</td>
<td>0.5647</td>
<td>0.6099</td>
</tr>
<tr>
<td>9</td>
<td>0.6342</td>
<td>0.4910</td>
<td>0.5803</td>
<td>0.6566</td>
</tr>
<tr>
<td>10</td>
<td>0.6176</td>
<td>0.5714</td>
<td>0.6278</td>
<td>0.6290</td>
</tr>
<tr>
<td>Avg</td>
<td><strong>0.6190</strong></td>
<td><strong>0.54104</strong></td>
<td><strong>0.5926</strong></td>
<td><strong>0.6205</strong></td>
</tr>
</tbody>
</table>

Figure 8. Tree for Relationship Age less than Two Years
To examine the predictive value of the service quality assessment variables, we let the logit models estimate the odds of defection of the newer SME customers with the relationship age of two years or less. Table 10 shows that in this case, the model with merely rational/boundedly-rational service quality assessment variables yields the highest predictive accuracy. Figure 8 depicts a decision tree which is trained by the SMEs with the relationship age of two years or less. The tree corroborates the importance of Total Pain (TP) variables (i.e. $R_j$s in the logit models) in predicting the SMEs behavior. It should be noted that even modest AUC scores (i.e. greater than 0.6) may yield good business results in the context of B2C churn (Provost & Fawcett 2013). Modest AUC scores deserve even more attention in the B2B service operations since the field is characterized by fewer customers but with more transactions and more revenue per transaction (Rauyruen & Miller 2007).

These results have important implications. While the overall predictive model is dominated by key control variables, restricting the focus to newer customers (for whom we have the complete service transactions and quality information) brings out the predictive value of the service pain assessment variables. Often these new customers are the ones with which firms do not yet have deep relationships, making it particularly important for operational analytics-driven methods. The fact that for these customers also it is the total pain that matters is an important finding for service organizations.
CHAPTER FIVE: USING SKYLINES TO OPTIMIZE MULTI-ATTRIBUTE DECISION ANALYTICS

“When once you have tasted flight, you will forever walk the earth with your eyes turned skyward, for there you have been, and there you will always long to return.” Leonardo da Vinci

This chapter pushes the dissertation essence to its apex; it highlights the behavioral economics hypotheses that can only be tested with the state-of-the-art database algorithms.

In chapter three we drew on the findings of the Heuristics and Biases research program and proposed an adaptive toolbox— as a bundle of computationally efficient decision rules that the economic agents might use to make decision on loyalty/ churn. In a simplistic scenario, an agent might follow a heuristic that is projected with respect to an individual SQI (as a decision factor) and subsequently churn. In this case, it is not difficult to inspect the evidence of the exercise of the decision rule. However, complications arise in the search for possible applications of one (or several) decision rules orchestrated on different combinations of SQIs.
A simple example can illuminate the subject matter of this chapter: Let us suppose that in a specific week, an agent experiences one unit of service failure regarding SQI1, and one unit of service failure regarding SQI2. Although the peak pain decision rule does not hold for the individual SQIs (since the prior peak pain regarding SQI1 and SQI2 is greater than one), it can be argued that the agent might follow the same decision rule that is orchestrated on <SQI1, SQI2>; since this is the first time that she is experiencing the <1, 1> service pain combination. In a similar vein and with the dimensionality of ten (i.e. SQI1, SQI2...SQI10), the simplistic scenario would only concern the application of ten peak service pain decision rules (i.e. peak service pain decision rule with respect to ten individual SQIs). Yet, this single decision rule can be orchestrated on 1013 (i.e. $2^{10} - 10 - 1$) different combinations of SQIs. Such exponential increase in the number of orchestrated decision rules becomes vitally important in the presence of big data—where the search space for evidence is expanded to thousands of customers, each with hundreds of decision points. In this chapter, we show the potentials of adopting a newly introduced concept in database research to tackle the problem of discovering adaptive toolbox orchestration mechanisms—which is yet unknown in the Fast and Frugal heuristics research program. In the presence of large databases on instant experience, effective and efficient methods of capturing potential orchestrated heuristics could help optimize decision analytics.
5.1. Skylines and Multi-Criteria Decision Making

The problem discussed above essentially concerns finding Pareto optimal sets, which has a half century history of research under different headings: admissible points distribution (Barndorff-Nielsen and Sobel 1966), maximal vector problem (Kung et al. 1975), and multi-objective optimization (Steuer 1986). The introduction of the Pareto optimal set discovery problem into database research where the algorithm efficiency is of the essence was not unexpected. Prior to 2001, there were three related topics in database research; namely nearest-neighbor queries, convex hulls, and top-k queries (e.g. Chang et al. 2000).

Regarding the nearest-neighbor queries, Roussopoulos et al. 1995 proposed an R-tree algorithm to extract the nearest neighbor object to a specific point and subsequently generalized the algorithm to find the K-nearest neighbors to a query point and report them in the ascending order.

A convex hull can be viewed as the periphery around the point set and is intuitively extracted if we span a rubber band around the points (Böhm and Kriegel 2001). Böhm and Kriegel (ibid.) proposed two algorithms to extract the convex hull in multidimensional data bases.

Top-k queries are meant to search the data for the best objects with respect to a ranking function (e.g. the best objects with respect to \( f(x,y,z) = x+y+z \) in a three-dimensional space). Chang et al. (2000) described the onion indexing as an indexing structure that can
facilitate top-\(k\) queries. The onion technique essentially constructs convex hulls in different layers similar to the onion structure.

Borzsonyi et al. (2001) was the first database research group that proposed two in-memory algorithms to extract the most interesting objects which are not dominated by any other object in a multi-dimensional space. By definition, the object \(t_1\) dominates the object \(t_2\) iff (if and only if) \(t_1\) is as good as or better than \(t_2\) with respect to all the dimensions, and is strictly better than \(t_2\) with respect to at least one dimension. The set of the objects that are not dominated by any other object form the skyline of the dataset, and such objects are referred to as the skyline objects. The classic example in database research concerns a holiday trip to Bahamas, where the traveler favors cheap hotels that are close to the beach. Consistent with the traveler’s perspective, Hotel ‘A’ dominates Hotel ‘B’ iff: \((A.\text{Distance} \leq B.\text{Distance} \land A.\text{Price} \leq B.\text{Price}) \land (A.\text{Distance} < B.\text{Distance} \lor A.\text{Price} < B.\text{Price})\)

That is, Hotel ‘A’ will be a better choice than Hotel ‘B’ if \(A.\text{Distance} \leq B.\text{Distance}\) and \(A.\text{Price} \leq B.\text{Price}\) and an inequality holds with respect to at least one dimension. Every hotel that is not dominated by any other hotel will be included in the set of the travelers optimal choices—i.e. the hotels skyline. Figure 1 depicts the skyline of the corresponding two-dimensional dataset, where the skyline hotels are depicted by solid circles.
Figure 9. Hotels Skyline

Borzsonyi et al. (2001) took one step further and highlighted the importance of this concept in database research by suggesting an SQL syntax for skyline queries. As an illustration, the suggested SQL query that would return the skyline hotels in Bahamas that are both cheap and close to the beach is:

```sql
SELECT * FROM Hotels
WHERE city = 'Bahamas'
SKYLINE OF price MIN, distance MIN;
```

5.2. Skylines and Orchestrated Heuristics

Now let us adopt the illustrative example in Figure 9 in the context of this dissertation: In a two-dimensional space (e.g. SQI1 and SQI2), the decision point (i.e. transaction week) \( w_1 \) dominates the decision point \( w_2 \) if the service pain experienced in \( w_1 \) is as bad as or worse than the service pain experienced in \( w_2 \) with respect to both SQIs and is strictly worse than \( w_2 \) with respect to at least one SQI. Consistently, the solid points
in Figure 10 form the service pain skyline of this two-dimensional dataset; i.e. the decision weeks that are not dominated by any other decision weeks with respect to the magnitude of the service pain experienced.

![SQI Pain Skyline](image)

**Figure 10. SQI Pain Skyline**

In the context of the heuristics and adaptive toolbox, the skyline in Figure 2 consists of the decision weeks where the peak pain decision rule holds with respect to both SQI1 and SQI2. That is, the agent has not experienced a service pain worse than the one she has experienced in \( w_4, w_7, w_9, w_{12}, \) and \( w_{14} \) with respect to both SQI1 and SQI2. In a time series dataset (e.g. an extensive record of instant utilities), however, this skyline changes as time goes by. Consistently, Figure 2 is a *snapshot* of the peak pain heuristic with respect to both SQI1 and SQI2 in \( w_{20} \). It should be noted that in the skyline literature ‘\(<\)’ (i.e. less than) determines the dominance, whereas in the context of pain heuristics the dominance factor is ‘\(\geq\)’ (i.e. greater than).
It is important to note that none of the decision weeks on the skyline dominates the others. In the above example, $w_4$ is the week where the customer experienced the peak pain with respect to SQI1, and $w_9$ is the week where she experienced the peak pain regarding to SQI2. That is, a churn that follows $w_4$ and $w_9$ might be simply attributed to the application of the peak pain heuristic. In the context of adaptive toolbox orchestration, however, $w_7$, $w_{12}$, and $w_{14}$ also become critical decision points although the customer has not experienced the peak pain with respect to a single SQI. An example that highlights the importance of such skyline objects concerns the NBA player Michael Jordan: As probably the most famous basketball player in history, Jordan does not hold any record with respect to any individual attribute in 1988; however, his performance is on some attributes skyline (example adopted from Pei et al. 2006).

Yet to fully inspect the application of an orchestrated heuristic in a multi-dimensional decision space, analyzing the full-space skyline is certainly not sufficient. The reason is that the conditions of a heuristic decision rule might hold with respect to a decision *subspace*; i.e. if the decision rule is orchestrated on a subspace of SQIs. In a ten-dimensional decision space, to illustrate, in addition to ten single SQIs and one full-space skyline, 1012 subspace skylines should be inspected. In a time series dataset (e.g. an extensive record of instant utilities), however, this is not a one-time process for each economic agent. In a two-year dataset (the case of this dissertation), an agent might have 105 decision weeks to make decisions on churn/loyalty. In order to inspect the role of the
heuristics in decision making, for every agent we need to check to see whether a decision week is located on any of the 1023 skylines, subsequently update the skylines, and proceed to the next decision week to repeat the whole process (see Chapter 4 for example). This, in fact spotlights the algorithm efficiency: Thousands of decision agents, each with a hundred decision points, and a thousand of multi-dimensional decision spaces.

In a TODS\textsuperscript{1} paper, Pei et al. (2006) blended the idea of skyline with the notion of datacube in data warehousing and materialized the idea of skycube, which consists of all subspace skylines of a multi-dimensional space. They also suggested a framework to compute the skycube. In addition to the questionable efficiency of updating the skycube (which is vitally important in the context of time series datasets), the question at this point is if the skycube notion is an effective means for discovering potential adaptive toolbox orchestration mechanisms. We try to answer this question in the next section.

5.3. Orchestrated Heuristics and Skycubes: What is Missing?

To answer the effectiveness of skycube as a means of investigating adaptive toolbox orchestration mechanisms let us consider the illustrative example in Figure 2 again. Although all solid points are skyline objects, there is an important difference between the semantics of \{w_4, w_9\} and \{w_7, w_{12}, w_{14}\}. To wit, \(w_4\) is the week that the agent

\textsuperscript{1} ACM Transactions on Database Systems
experienced a peak pain with regard to SQI1 and a minimum pain with regard to SQI2. Likewise, \( w_9 \) is the week that the agent experienced a peak pain with regard to SQI2 and a minimum pain with regard to SQI1. Specifically, \( w_4 \) and \( w_9 \) are on the \( sky < SQI1, SQI2 > \) (i.e. full-space skyline) because they are on \( sky < SQI1 \) and \( sky < SQI2 \) respectively.

However, from the adaptive toolbox perspective where the focus is on the fast and computationally efficient heuristics, a churn (or any decision) following \( w_4 \) or \( w_9 \) might not be attributed to a heuristic orchestrated on SQI1 and SQI2 although both weeks are on \( sky < SQI1, SQI2 > \). Rather, a churn following to \( w_4 \) might be attributed to the peak pain heuristic only with respect to SQI1—highlighting the importance this service quality index. Likewise, a defection subsequent to \( w_9 \) will only highlight the importance of SQI2. A churn subsequent to \( w_7, w_{12}, \) or \( w_{14}, \) however, addresses the importance of this decision heuristic orchestrated on the combination of SQI1 and SQI2. Intuitively, in a two-dimensional space we are interested in the two-dimensional skyline weeks that have not inherited their importance from any single-dimensional skyline.

This becomes complex as the number of pain dimensions (e.g. SQIs) increases. Consider for example Table 11 (Table adopted from Xia et al. 2012), which concerns the weekly pains that an agent experienced with regard to four SQIs during nine weeks of service after the base week (e.g. week 24 in this dissertation). The base week’s SQIs are the maximum service pains that the decision agent has experienced until that week.
In week nine (w9) after the base week, the service pain skycube of this decision agent (Table 12) is comprised of fourteen subspace skylines and one full-space skyline. Among the subspace skylines the single-dimensional ones are those that we have already investigated in Chapter Four (see Figure 7 more details).

**Table 11. Weekly Service Pain Scenario**

<table>
<thead>
<tr>
<th></th>
<th>SQI1</th>
<th>SQI2</th>
<th>SQI3</th>
<th>SQI4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base Week</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>week 1</td>
<td>7</td>
<td>6</td>
<td>8</td>
<td>5</td>
</tr>
<tr>
<td>week 2</td>
<td>6</td>
<td>4</td>
<td>3</td>
<td>8</td>
</tr>
<tr>
<td>week 3</td>
<td>1</td>
<td>3</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>week 4</td>
<td>6</td>
<td>7</td>
<td>4</td>
<td>9</td>
</tr>
<tr>
<td>week 5</td>
<td>8</td>
<td>8</td>
<td>7</td>
<td>9</td>
</tr>
<tr>
<td>week 6</td>
<td>4</td>
<td>9</td>
<td>9</td>
<td>7</td>
</tr>
<tr>
<td>week 7</td>
<td>9</td>
<td>7</td>
<td>6</td>
<td>9</td>
</tr>
<tr>
<td>week 8</td>
<td>4</td>
<td>5</td>
<td>7</td>
<td>2</td>
</tr>
<tr>
<td>week 9</td>
<td>8</td>
<td>8</td>
<td>7</td>
<td>3</td>
</tr>
</tbody>
</table>

In the above skycube beside the single-dimensional skylines (which could be discovered without the notion of skyline), <SQI1, SQI2> and <SQI1, SQI3> are the only

**Table 12. Service Pain Skycube**

<table>
<thead>
<tr>
<th>SQI Subspace</th>
<th>SQI Skyline</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;SQI1&gt;</td>
<td>w7 (i.e. week 7)</td>
</tr>
<tr>
<td>&lt;SQI2&gt;</td>
<td>w6</td>
</tr>
<tr>
<td>&lt;SQI3&gt;</td>
<td>w6</td>
</tr>
<tr>
<td>&lt;SQI4&gt;</td>
<td>w4, w5, w7</td>
</tr>
<tr>
<td>&lt;SQI1, SQI2&gt;</td>
<td>w5, w6, w7, w9</td>
</tr>
<tr>
<td>&lt;SQI1, SQI3&gt;</td>
<td>w1, w5, w6, w7, w9</td>
</tr>
<tr>
<td>&lt;SQI1, SQI4&gt;</td>
<td>w7</td>
</tr>
<tr>
<td>&lt;SQI2, SQI3&gt;</td>
<td>w6</td>
</tr>
<tr>
<td>&lt;SQI2, SQI4&gt;</td>
<td>w5, w6</td>
</tr>
<tr>
<td>&lt;SQI3, SQI4&gt;</td>
<td>w5, w6</td>
</tr>
<tr>
<td>&lt;SQI1, SQI2, SQI3&gt;</td>
<td>w1, w5, w6, w7, w9</td>
</tr>
<tr>
<td>&lt;SQI1, SQI2, SQI4&gt;</td>
<td>w5, w6, w7</td>
</tr>
<tr>
<td>&lt;SQI1, SQI3, SQI4&gt;</td>
<td>w1, w5, w6, w7</td>
</tr>
<tr>
<td>&lt;SQI2, SQI3, SQI4&gt;</td>
<td>w5, w6</td>
</tr>
<tr>
<td>&lt;SQI1, SQI2, SQI3, SQI4&gt;</td>
<td>w1, w5, w6, w7</td>
</tr>
</tbody>
</table>
subspaces that should be investigated with regard to orchestration mechanisms. Specifically, of the eleven multi-dimensional skylines in the skycube nine could not serve as the evidence of the orchestrated heuristics decision application.

\[ \text{sky} < \text{SQI}_1, \text{SQI}_3, \text{SQI}_4 > \] is an illustrative example for the nine multi-dimensional skylines that are not informative with regard to potential orchestration mechanisms. The skycube indicates that the decision agent experienced peak pain with regard to this specific subspace in weeks 1, 5, 6, and 7 after the base week. Yet, all of these weeks inherit their importance from being on \( \text{sky} < \text{SQI}_3 > \), \( \text{sky} < \text{SQI}_4 > \), and \( \text{sky} < \text{SQI}_1, \text{SQI}_3 > \). In the context of heuristics, a churn following the first week (week 1) after the base week would highlight the application of peak pain orchestrated on \( <\text{SQI}_1, \text{SQI}_3> \) rather than \( <\text{SQI}_1, \text{SQI}_3, \text{SQI}_4> \).

Even on \( <\text{SQI}_1, \text{SQI}_2> \) and \( <\text{SQI}_1, \text{SQI}_3> \) as the subspaces that include potential applications of orchestrated heuristics, we are only interested in the weeks whose existence on the corresponding skylines are not inherited from the lower-level skylines. For \( \text{sky} < \text{SQI}_1, \text{SQI}_2 > \), weeks 6 and 7 inherit their importance from \( <\text{SQI}_2> \) and \( <\text{SQI}_1> \) respectively; leaving weeks 5 and 9 to investigate for a potential orchestration mechanism. Similarly among the five weeks on \( \text{sky} < \text{SQI}_1, \text{SQI}_3 > \), only weeks 1, 5, and 9 should be investigated for the application of orchestrated peak pain heuristic.

Intuitively, for each service week in the service pain skycube we are interested in the smallest subspaces that the week is on the skyline; which is the missing piece of the
skycube framework as a means for investigating the evidence of orchestrated heuristics application.

The above example illuminates why skycube is not an efficient means of investigating adaptive toolbox orchestration mechanisms either: To incorporate the notion of orchestrated heuristics in a ten-dimensional service quality space and over two years of service, as we move the sliding window\(^2\) one week for a customer, we have to update the service pain skycube. For every skyline within the specific week’s service pain skycube, we then need to make sure that each skyline week is not located on any corresponding subspace skyline. To wit, for a specific customer and within a specific week there exists a specific service pain skycube. Among the 1012 skylines of the specific service pain skycube and for a specific eight-dimensional skyline we need to check 254 (i.e. \(2^8-1-1\)) subspace skylines to make sure that they do not hold any of the eight-dimensional skyline weeks. Moreover, this process has a very expensive space cost. Again, there are nearly one hundred thousand customers in the service database each with a service episode that could extend to over one hundred weeks.

The findings of this dissertation put more stress on the time complexity of updating the customer’s service pain skycube. We have shown that service organizations must be alert to heuristics that might exacerbate the impact of total service pain on

\(^2\) See Section 4.1 where we register if a decision rule condition holds with respect to the current location of sliding window and move the sliding window until the end of the service episode
customer’s decision to churn. Accounting for orchestrated heuristics, this means that as a customer experiences service failures her service pain skycube should be updated instantly. The customer’s updated service pain skycube could alert the service organization that a peak pain heuristic is just orchestrated for the customer; calling for intervention before churn.

In the next section we show how a new framework for online subspace skyline query processing (Xia et al. 2012) could be adopted for investigating any evidence of orchestrated heuristics application in the context of this dissertation.

5.4. Compressed Skycubes and Adaptive Toolbox Orchestration Mechanisms

To facilitate the real-time processing of subspace skyline queries, Xia et al. (TODS, 2012) suggested the idea of compressed skycube as a lossless compression of the original skycube suggested by Pei et al. (TODS, 2006). Instead of all subspace skylines, a compressed skycube stores the minimum skylines in addition to the full-space skyline. Although the notion of minimum skyline is essentially proposed to alleviate the time and space complexities of updating skycubes, it is also an effective means of the search for adaptive toolbox orchestration mechanisms: The minimum skyline of a subspace is the subset of the skyline objects in that subspace that are not the skyline objects of any proper subset of the subspace. Table 13 shows the compressed skycube of the service pain scenario in this chapter (see Table 11).
Table 13. Service Pain Compressed Skycube

<table>
<thead>
<tr>
<th>SQI Subspace</th>
<th>SQI Minimum Skyline</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;SQI1&gt;</td>
<td>w7</td>
</tr>
<tr>
<td>&lt;SQI2&gt;</td>
<td>w6</td>
</tr>
<tr>
<td>&lt;SQI3&gt;</td>
<td>w6</td>
</tr>
<tr>
<td>&lt;SQI4&gt;</td>
<td>w4, w5, w7</td>
</tr>
<tr>
<td>&lt;SQI1, SQI2&gt;</td>
<td>w5, w9</td>
</tr>
<tr>
<td>&lt;SQI1, SQI3&gt;</td>
<td>w1, w5, w9</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>SQI Fullspace</th>
<th>SQI Fullspace Skyline</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;SQI1, SQI2, SQI3, SQI4&gt;</td>
<td>w1, w5, w6, w7</td>
</tr>
</tbody>
</table>

The Lossless-Compression Theorem in Xia et al. (2012) proves that the compressed skycube is a lossless compression of the skycube; that any subspace skyline can be computed from the minimum skylines that are stored in the compressed skycube. In this vein, the QueryCSC algorithm receives the subspace dimensions and the compressed skycube as the two inputs and return the skyline of the input subspace. To investigate the application of orchestrated heuristics, however, all we need is the minimum subspace skylines that are already stored in the compressed skycube. It should be noted that QueryCSC algorithm is still necessary as it is invoked by other algorithms for calculating the minimum skylines.

Another notion proposed by Xia et al. (2012) is minimum subspace. In the context of service quality adaptive toolbox, a SQI subspace $S$ is a minimum subspace of a service week $w$, iff $w$ is a member of the minimum skyline of $S$. This is literally the missing piece in section 4.3; i.e. “minimum subspaces of a skyline object are the smallest subspaces...
where the object is in the skylines”. (Xia et al. 2012, p. 19) The set of minimum SQI subspaces of a week \( w \) is denoted by \( mss(w) \).

We posit that the minimum subspaces set cardinality plays a significant role in discovering any evidence of adaptive toolbox application in organizational decision making. Consistently, we have added three columns that reflect the cardinality concept to the minimum subspaces set table (Table 14).

**Table 14. Minimum Subspaces Set Cardinality**

<table>
<thead>
<tr>
<th>Service Week</th>
<th>SQI Minimum Subspaces Set</th>
<th>Cardinality</th>
<th>Overall</th>
<th>Single-Dimensional</th>
<th>Multi-Dimensional</th>
</tr>
</thead>
<tbody>
<tr>
<td>w1</td>
<td>(&lt;\text{SQI1, SQI3}&gt;)</td>
<td></td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>w4</td>
<td>(&lt;\text{SQI4}&gt;)</td>
<td></td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>w5</td>
<td>(&lt;\text{SQI4}, \text{SQI1, SQI2}, \text{SQI1, SQI3}&gt;)</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>w6</td>
<td>(&lt;\text{SQI2, SQI3}&gt;)</td>
<td></td>
<td>2</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>w7</td>
<td>(&lt;\text{SQI1}, \text{SQI4}&gt;)</td>
<td>2</td>
<td>2</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>w9</td>
<td>(&lt;\text{SQI1, SQI2}, \text{SQI1, SQI3}&gt;)</td>
<td>2</td>
<td>0</td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

According to Table 14, the customer experienced one incident of peak pain orchestrated on \(<\text{SQI1, SQI3}>\) in the first week after the base week and no peak pain in weeks two and three. The fifth week after the base week (i.e. \( w5 \)) has been the worst week in terms of peak pain where the customer experienced three incidents of peak pain (i.e. \( |mss(w5)|_{\text{overall}}=3 \)). It is noteworthy again that consistent with the notion of minimum subspaces, we are confident that \( mss(w5) \) includes the smallest SQI subspaces where the customer experienced peak service pains on in the fifth week after the base week. In this vein, one incident corresponds to a peak pain with regard to SQI4 (i.e. \( |mss(w5)|_{\text{single-}} \).
and two incidents address the peak pains orchestrated on different dimensions (i.e. \(| mss(w) |_{\text{multi-dimensional}} = 2 \)).

5.5. Minimum Subspaces and Behavioral Decision Analytics

We posit that Table 14 and its variants lay the groundwork for rigorous testing of any hypothesis regarding the role of heuristics in decision making, especially in the presence of big data. Drawing on the heuristics and biases literature, in this section we propose a few such hypotheses in the context of this dissertation; i.e. organizational decision making on churn. Subsequently we demonstrate how Table 14 and its variants can be used to test the hypotheses. Needless to say, any hypothesis that passes the test in the descriptive analysis could be applied to building a predictive model for organizational decision making (see Chapter Four for example).

To investigate the behavioral economics hypotheses in this section we suggest employing a matched sampling similar to the one suggested in Chapter Four; where the service episodes of non-churners are selected based on the service episodes of the corresponding churners. Specifically, for every churner we randomly select a group of non-churners (that have not been selected by the process yet) whose initial service episodes are longer that the churner’s. Subsequently, we select their service episodes so that (i) the ending of the episodes coincides with the churner’s and (ii) their episodes’ length is equal to the churner’s.
The first behavioral hypothesis concerns the overall role of peak pain heuristic in a multi-dimensional service quality space; e.g. service peak pain has a positive relationship with churn. It is noteworthy that here, compared to the majority of IS research, we are focusing on the actual churn and not intention to churn. This is again in line with Friedman’s (1953) perspective to the importance of real observed behavior of the firm; “what they do instead of what they say they do.” Consider H1 as a simplified example for this hypothesis. In the next section we elaborate why we note ‘simplified’ for the proposed hypotheses.

**H1. Service customers’ odds of attrition is positively associated with the instant service peak pain they experience.**

Having Table 14 extracted and selecting the last six weeks of service episode as the action window (see Chapter Four), for each customer we need to first extract
\[ M_{H1,overall} = \sum_{t=T-5}^{T} |mss(w_t)|_{overall}; \]
where \( T \) is the last week number in the customer’s service episode. This is the number of times that the customer has experienced peak pain with respect all different combinations (both single-dimensional and multi-dimensional) of SQIs during the last six weeks in her service episode. To test the first hypothesis, an ANOVA could be conducted with two treatments (i.e. churners versus non-churners) on \( M_{H1,overall} \) as the dependent variable. The analysis of variance can reveal if on average, churners have significantly experienced more service peak pain in the last six weeks of their service episodes than non-churners.
Using $M_{H1,\text{overall}}$ to examine the significance of $H1$ assures us that we have considered all possible combinations on which the peak pain heuristic might be orchestrated.

The second behavioral economics hypothesis that can be investigated with Table 14 concerns the evidence of adaptive toolbox orchestration mechanisms; i.e. if orchestrated heuristics matter in organizational decision making. Consider $H2$ as a simplified example:

$H2$. Service customers’ odds of attrition is positively associated with the instant service peak pain orchestrated on two or more service quality dimensions.

To test this hypothesis, two measures should be extracted from Table 14 for each customer; 

$$M_{H2,\text{single}} = \sum_{t=T-5}^{T} |mss(w_t)|_{\text{single-dimensional}}$$
and

$$M_{H2,\text{multiple}} = \sum_{t=T-5}^{T} |mss(w_t)|_{\text{multi-dimensional}}.$$  

First, an omnibus MANOVA could reveal if the vector of these measure, i.e. $[M_{H2,\text{single}}, M_{H2,\text{multiple}}]$, is significantly different for churners; and if yes, follow-up ANOVAs can demonstrate whether churners have significantly experienced more orchestrated service peak pain in the last six weeks of their service episodes than non-churners; or if only single-dimensional service peak pain matters. In case $M_{H2,\text{multiple}}$ is found to be significantly greater for churners than for nonchurners, we can infer that the decision rules in the hypothesized organizational adaptive toolbox can be applied to organizational decision making in an orchestrated fashion.
Another group of behavioral hypotheses concerns the maximum dimensionality of adaptive toolbox orchestration mechanisms with respect to organizational decisions on churn. That is, what is the maximum number of dimensions on which the service peak pain could be orchestrated in a way that significantly affects organizational decisions on churn? H3 is a simplified example for this series of hypotheses:

\[ H3. \textit{Service customers' odds of attrition is positively associated with the instant service peak pain orchestrated on three or more service quality dimensions.} \]

This could be viewed as a sensitivity analysis on the number of orchestration dimensions. Again, a variant of Table 14 can facilitate this analysis. Specifically, we need to drill down on the cardinality of Table 14; e.g. having tuples like <..., \textit{Single Dimensional Cardinality}, \textit{Two Dimensional Cardinality}, \textit{Three and More Dimensional Cardinality}>. We suspect this is an important research question in the context of heuristics and biases. That is, the hypothesis addresses the limitations on the orchestration mechanisms of the adaptive toolbox decision rules, which are hypothetically invoked when at least one of the information processing limitations is in place.

5.6. Compressed Skycube and Adaptive Toolbox Orchestration; Still a Missing Piece

In the previous section we proposed a series of simplified heuristics on adaptive toolbox orchestration mechanisms that can be potentially examined using the compressed skycube framework. We note ‘simplified’ because as we saw in Chapter
Four, a customer might have experienced service peak pain just before she churned; yet, it could be the case that the same customer had not churned previously although there were several occasions where she experienced orchestrated service peak pain.

Single dimensional analysis of service pain in Section 4.2.1 can explain this phenomenon. To wit, 10.4% of churners have experienced peak proportional pain corresponding to \([\text{DR3}, SQI_2(\bar{p}_t)]\) in their last six weeks prior to defection, while this number is 7.6% for non-churners (i.e. \(\frac{10.4\%}{7.6\%} = 1.37\)). Yet, about 50% of the churners in the numerator did not follow the same decision rules more than 4 times within their service episodes. That is, the same decision rule had set off an alarm but they did not churn subsequently.

The present compressed skycube framework only updates the compressed skycube subsequent to a change to the base table. In the context of our research, however, we need to store a snapshot of the minimum subspaces cardinality table (Table 14) following each service week to further examine the role of orchestrated adaptive toolbox heuristics on the final decision to churn. Specifically, we are dealing with a history (i.e. time series) of SQI minimum subspaces sets. To wit, we are searching to answer why a customer did not churn following a service peak pain orchestrated on a number of service quality indexes; yet churned following another service pain orchestrated on other service quality indexes.
Answering the above question is crucially important from the perspective of predictive analytics of organizational decisions on churn as the crux of this dissertation. That is:

- Is there a specific subset of SQIs (among the 1013 available subsets in a ten-dimensional service space) on which an orchestrated service pain would increase the odds of churn?
- Is there a specific service pain compressed skycubes time series (i.e. a compressed skycubes pattern over time) which eventually leads to churn significantly more than other patterns?
- Does the number of times that a customer experiences orchestrated service peak pain affect the odds of her churn?
- Is there a specific subset of service quality indexes whose frequency of corresponding orchestrated service peak pain during the whole episode increases the odds of defection?

The answers to the above questions have the potential to improve the accuracy of predictive models for organizational decisions; e.g. in the single-dimensional analyses in this dissertation (see Section 4.3.) one of the significant predictors in all rounds is number of times that the extensional end pain heuristic (with \( \bar{p}_t \)) holds with respect to SQI2 (i.e. \( H_{13} \)).

Not only are these important research questions from the two perspectives of predictive analytics of decisions and behavioral economics, we also suspect that they
could be an extension of the compressed skycube query processing with time as an inherent dimension of the queries.

Regarding the SQL implementation of the framework, storing the compressed skycube with two sets of \(<\text{SME\_ID}, \text{Week\_ID}, \text{Minimum\_Subspace\_ID}>\) tuples would facilitate extracting Table 13 and Table 14, along with a history of each table for each SME using simple SQL Select statements. Specifically with the two sets of tuples (i.e. SME\_Last\_CSC and SME\_Dynamic\_CSC) we would be able to (i) examine the hypotheses proposed in Section 5.5, (ii) calculate which week has been on how many minimum skylines throughout the customer’s service episode, and (iii) calculate the number of times a minimum pain subspace has been provoked in the whole episode. The key difference between the two sets of tuples is that SME\_Last\_CSC always carries the latest compressed skycube of each SME, whereas SME\_Dynamic\_CSC keeps the complete history of changes in the minimum skylines. The following pseudo code illustrates the subtle differences in the process:

For each SME,
  Fetch the SME’s service episode; i.e. \([w_{\text{start}}, w_{\text{end}}]\),
  Use \(BUCSC\) to extract and store the SME’s compressed skycube for \([w_{\text{start}}, w_{\text{start}+23}]\) as the base in both SME\_Last\_CSC and SME\_Dynamic\_CSC,
  For each \(w_i\) in \([w_{\text{start}+24}, w_{\text{end}-5}]\),
    If \(w_i\) is on a minimum skyline,
      \textbf{Insert} the corresponding tuples into SME\_Last\_CSC and SME\_Dynamic\_CSC,
      \textbf{Delete} the corresponding dominated weeks in SME\_Last\_CSC,
    // Do not delete any dominated weeks in SME\_Dynamic\_CSC,
This dissertation is one of the first studies that suggests drawing on the idea of compressed skycubes in database research to discover any evidence of the existence of adaptive toolbox orchestration mechanisms. We have demonstrated how the minimum subspaces set cardinality (Table 14) could facilitate examining different hypotheses regarding the potential role of orchestrated heuristic decision rules in decisions on churn/loyalty. As a hypothesis turns out to be significant, one can employ the corresponding predictor as part of the churn predictive model (see Chapter Four for example).

We have laid the groundwork for implementing the TODS framework for compressed skycube query processing (Xia et al. 2012) in SQL Server; yet, we will pursue the research questions in this chapter following acquiring a relevant database.
CHAPTER SIX: CONCLUSIONS

“Isolated discrepancies with this potential occur so regularly that no scientist could bring his research problems to a conclusion if he paused for many of them.” (Kuhn 1961, p. 178)

In this dissertation we have analyzed a large B2B service database to examine the predictive value of rational/boundedly-rational models of service quality assessment with regard to organizational decisions on loyalty. To the best of our knowledge, this is one of the first studies to investigate this subject matter in behavioral organizational analytics using continuous and granular records of instant utilities over prolonged periods (i.e. two years). The following list provides a high-level summary of the contributions of the dissertation to the disciplines that it has drawn on:

- Inspired by cognitive science and behavioral economics the present dissertation highlights the virtues of employing a hybrid deductive/inductive approach to analyze and predict organizational decisions. This is one aspect of the dissertation that we refer to as theory driven data analytics.

- Inspired by an important problem in B2B service operations (i.e. predicting customers attrition) and using a large repository of B2B real-time...
transactional data with service quality indicators, this dissertation puts the utility and heuristic models to the test of accuracy. Despite the highlighted importance in behavioral operations and behavioral economics, the predictive accuracy of such models has been rarely investigated in either of the fields (Katsikopoulos & Gigerenzer 2013).

• The findings of this dissertation have demonstrated that the assumed rationality and practical omniscience of organizations can help yield accurate predictions about their future decisions in uncontrolled experiences and in the presence of large empirical data.

• The dissertation’s findings show that assuming that an adaptive toolbox (as a set of heuristic decision rules) is employed in organizational decision making can help improve the accuracy of predictions about the subsequent organizational decisions. As an illustration, the findings demonstrate that selected boundedly-rational decision rules appear to cause somatic states that make organizations more sensitive to past total qualities of service (For recent examples see Sull and Eisenhardt 2015).

• The present dissertation is a response to the call in the B2B Agenda Project (Wiersema 2013, p. 484) where there is a need to “fully understand and focus on what really has an impact on customers […] with greater granularity, faster, and more effectively.”
• As managerial implication for B2B service operations, the findings of the dissertation have shown that service organizations must be alert to heuristics that might exacerbate the impact of total service pain on customer’s decision to churn.

• This dissertation is one of the first B2B churn prediction studies that effectively relies on service quality related factors as predictors of attrition.

• In the same vein, this dissertation takes a unique labor-intensive approach for discovering churners and pinpointing their churn dates. Accordingly, it is one of the first churn analytics studies in noncontractual settings where churners have different service utility/pain episodes (compared to having a fixed prediction period; see Jahromi et al. 2014 for example). We also suggest and implement four different algorithms for pinpointing churn dates in noncontractual settings along with their accuracies benchmarked against the human expert opinion.

• The dissertation’s sensitivity analysis verifies the robustness of its findings.

• Last but not least, this dissertation is one of the first studies that has suggested a framework for discovering any evidence of the existence of adaptive toolbox orchestration mechanisms in the presence of large empirical data. To wit, we have adopted a state-of-the-art framework for compressed skycube projection in database research as a means of examining the
application of heuristic decision rules *orchestrated* on different service quality
dimension.

Sections 5.1 and 5.2. explain the dissertation’s implications for organizational
decision analytics and B2B service operations.

6.1. Implications for Organizational Decision Analytics

The findings of this dissertation are in line with Simon’s (1997a) speculations that
organizations use a “continuum of decision-making styles” that involve both analytical
and heuristic techniques. Regarding the analytical techniques, the results of both the
descriptive and predictive analyses suggest that the average behavior of SMEs as a group
is as if they are rational. That is, the rational measures of service pain assessment are
found to help yield accurate predictions about the SMEs’ subsequent decisions. This is in
line with Friedman’s (1953) perspective on the fruitfulness of a theory as evaluated by its
predictive accuracy. To achieve accurate predictions about the group (i.e. organizational)
behavior especially in the context of uncontrolled experiences and over long periods, we
need simplifying assumptions such as omniscient rationality. Yet, our findings should
not characterize SMEs as completely rational. What we have shown in this dissertation is
that, overall, the SMEs’ assumed omniscience and rationality appear to contribute to our
model’s statistical and practical significance. This is also consistent with those findings in
experimental economics that concur with neoclassical predictions. (e.g. List 2004)
Regarding the heuristic decision rules, the findings of this dissertation are consistent with Damasio’s (1994) somatic marker hypothesis and Kahneman & Frederick’s (2002) assumption regarding the dual-system of cognitive processes. That is, the biasing nature of heuristics might cause a somatic state which draws the SME’s attention to the service quality issues and subsequently calls for reasoning and judgment— which might be carried out in a relatively rational way. Specifically, the biasing nature of heuristics might be an “attentional mechanism” that can either realize or exacerbate the effect of rational service pain evaluation on subsequent decisions. In this sense, while the peak pain draws the SME’s attention to the corresponding service issue, the SME’s information systems may play the role of a working memory which is necessary for coherent analytical processing and reasoning after the somatic marker operates. (Bechara and Damasio 2005) Being in a somatic state caused by the peak pain, the organization carries out the subsequent evaluation more sensitively.

The significant role of the service peak pain on churn highlights the potential role of orchestration mechanisms that might be employed along with the heuristic decision rules in the hypothesized adaptive toolbox in organizational decision making. To wit, an agent might follow a heuristic decision rule that is projected with respect to an individual SQI and subsequently churn. In this case, it is not difficult to inspect the evidence of the exercise of the decision rule. Yet, complications arise in the search for possible applications of one (or several) decision rules orchestrated on different combinations of...
SQIs. In this vein, Chapter Five adopted a state-of-the-art algorithm in database research and proposed a framework for investigating any evidence of a mechanism that might orchestrate the heuristic decision rules in the organizational adaptive toolbox.

The highlighted role of omniscient rationality in our findings can be explained from the behavioral organizational economics standpoint. First, it can be argued that the neoclassical organizational decision-making is a special case of Simon’s bounded rationality (Sontheimer 2006) according to which individuals’ decisions are satisficing and not optimizing due to the limitations on information, analytical processing capacity, and time. Thus, the same purposeful individuals may make optimizing decisions in a situation void of these limitations. For example, it can be argued that the service quality information is being logged by the organization’s information systems. As a result, the necessary information is not low in accessibility, and hence waives the need to employ any heuristic. It should be noted, yet, that the general perception in behavioral economics is that “the information does not have to be processed just because it is there.” (Simon 1997a, p. 225) That is, even if the essential information is made available to a purposeful individual, her decisions will deviate from the optimizing ones. (Zauberman et al. 2006)

Regarding the limitations on processing capacities it can be argued that the analytical processing capacity of a group of decision makers in a SME should be able to outperform an individual’s. This, in fact, nominates the group as the basic decision unit in organizations as opposed to what has been proposed in behavioral economics. (Simon
To illustrate, Oliva and Watson (2009) demonstrate that group forecasting can improve the forecast accuracy by mitigating individual biases. Lastly, it can be assumed that SMEs spend enough time to contemplate ending a B2B relationship with a service company that might ultimately affect end customers. Each of these speculations deserves subtler investigation that could be undertaken by qualitative studies; which is beyond the scope of the present dissertation.

### 6.2. Implications for B2B Service Operations

We have demonstrated the virtues of deduction from cognitive science and economics in mining large granular B2B databases to gain deep insights about customer experience and how it affects loyalty. Specifically, the omniscient rationality assumption in neoclassical economics should be considered as it is meant to help yield accurate predictions about the group behavior in uncontrolled experiences. In this sense, the decision tree in Figure 8 illustrates that such theories can help even inductive machine learning methods yield more accurate predictions; i.e. total pain variables in the decision tree are extracted based on the omniscient rationality assumption. This is an important finding in B2B service operations management where the prior conception (Bolton et al. 2006) is that firms do not follow a rational model of service quality assessment (e.g. temporal integration) in making decisions about service renewals.
As a managerial implication for building stronger B2B relationships (Peppers & Rogers 2001), our findings suggest that the service company should constantly monitor the total quality of service that a customer is receiving and keep the total service pain low. In the midst of service failures, the service company should be alert to the heuristics (e.g. peak pain) that can cause a somatic state for the customer and makes her more sensitive to the past total service pain. There is also value in building predictive models separately for newer customers, the ones with whom the organization does not yet have a deep business relationship.

This also highlights the vital role of good information systems design. (Simon 1997a) Organizations must have access to systems that provide information and decision rules that encourage rational, evidence-based approaches to important decisions, such as how to maintain B2B relationships in the presence of large, real-time service BI databases. This may involve strengthening ties when service is excellent and weakening ties in response to problems. Good information systems design is central to both ways of responding in an agile manner. It should be noted, however, that this goes hand in hand with the effectiveness of administrators’ decision-making (Simon 1997a).

The highlighted effect of rational service pain assessment on SMEs’ decisions can be also explained from the B2B service operations standpoint. In the B2B setting, service pain and corresponding costs are presumably incurred by the SME and not the individual agents that make relevant decisions. In some situations, this phenomenon could lead to
moral hazard, where SME's bearing of the costs would entice the agents to make decisions that are not aligned with the company. (Kull et al. 2014) In the present study, however, it can be suggested that the fact that the agents do not directly incur the service pain allows them to make rational decisions from which the SME may actually benefit. Similarly, it can be speculated that if the costs of service lapses are imposed on decision makers directly, they might respond differently — probably through employing some of the heuristic decision rules discussed in this dissertation.

6.3. Limitations

The present dissertation is subject to a number of limitations. Most importantly, we do not have access to SMEs’ transactions with other service companies in the market — which might affect their decision on loyalty in a non-contractual environment. It is possible that some of these SMEs have been transacting with other service companies at the same time in the two year window. This would make our measures of instant utility incomplete — an issue we must acknowledge.

A second limitation concerns defection and its timing. We are not able to fully attribute a drop in service transactions to poor service quality as it might be the result of a business slowdown or even shutdown. Although the two mentioned limitations affect both rational and heuristic models in this dissertation equally, it might be argued that the subjective nature of defection timings could bias the results against the latter. That is, the
recency of the discussed heuristics makes them more dependent on the episode ending. To partially alleviate this concern in our search for the applications of heuristic we used a six-week sliding window.

Another limitation concerns the heuristic decision rules and their implementation. This is especially important considering the highlighted role of such decision rules and the somatic states they cause. Behavioral economists can always suggest different materializations of these heuristics and more importantly, suggest new heuristics in organizational decision-making. This will be an important future research direction in service management since databases of service BI information are becoming more available to organizational decision makers. (Roth and Menor 2003, Metters & Marucheck 2007)

Finally, although this dissertation is one of the first studies that has made a connection between adaptive toolbox orchestration mechanisms and compressed skycube query processing, and despite the fact that we have laid the groundwork for implementing the framework for compressed skycube query processing in SQL Server, we could not investigate the corresponding research questions due to the unavailability of data.
6.4. Concluding Remarks

The findings of this dissertation, in our opinion, indicate that rationality in organizational decision analytics is not a zero-sum game for either behavioral or neoclassical economics. The findings suggest that in the context of organizational decisions and in the long run, where we are restricted to uncontrolled experiences, neoclassical assumptions on rationality appear to help us achieve accurate predictions. This is consistent with Friedman’s (1953) argument that “a theory can[not] be tested by the realism of its assumptions independently of the accuracy of its predictions.” On the other hand, despite what is postulated in neoclassical economics, our findings indicate that heuristics might be essential in the prediction of organizations’ behavior. That is, they might help organizations make rational decisions by causing somatic states that call for further rational evaluation of service qualities.
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APPENDIX A: ALGORITHM 4 FOR PINPOITING CHURN DATES IN A NONCONTRACTUAL SETTING

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For each customer, first we need to compute all the four-week aggregates in her episode. Think of it as moving a sliding 4-week window and extract sum of volumes based on its locus.

---

```
use Holistic

declare @SQL varchar(1000),
@customerID int,
@strcustomerID varchar(6),
@gold int,
@dateindex date,
@dateindex2 date,
@last date,
@columnname varchar(3),
@dateID int,
@goldchar varchar(4)

Declare CustomerCur cursor for
select distinct(customerID)
from [Holistic].dbo.HolisticVolumeIndexed
order by customerID
open CustomerCur
fetch CustomerCur into @CustomerID

while @@FETCH_STATUS=0
begin

select
@dateindex=t0.BizStartWeek,
```
@last=t0.BizendWeek
From [Holistic].dbo.CustomerBuinessDuration t0
where t0.CustomerID=@CustomerID

While @dateindex < dateadd(ww,-2,@last)
begin
Select @dateID=t2.DateID
from [Holistic].dbo.datebase t2
where t2.FirstDayOfWeek= @dateindex

set @columnname= convert(varchar(3), @dateID)
set @dateindex2=dateadd(ww,+3,@dateindex)

Set @strcustomerID =convert(varchar(6), @customerID)

SELECT @gold=sum(t1.[Volume])
FROM [Holistic].[dbo].[HolisticVolumeIndexed] t1
where t1.CustomerID=@customerID
and t1.[FirstDayOfWeek] between @dateindex and @dateindex2
group by t1.[CustomerID]

Set @goldchar =convert(varchar(10), @gold)

Select @SQL = 'Update [Holistic].[dbo].[4WeekWindowAggregation] set ['
+ @columnname + ']' = ' + @goldchar + ' where
[Holistic].[dbo].[4WeekWindowAggregation].CustomerID = ' +
@strcustomerID

exec(@sql)

set @dateindex=dateadd(ww,+1,@dateindex)

end
fetch CustomerCur into @CustomerID
end

close CustomerCur
deallocate CustomerCur

-**************************************************************************************************************
-**************************************************************************************************************
--For each customer, now we need to compute the differences --between adjacent windows...

Declare @BigIndex int=5,
@smallIndex int,
@strBigIndex varchar(6),
@strSmallIndex varchar(6),
@SQL varchar(1000)

While @BigIndex < 103
Begin
Set @SmallIndex=@BigIndex-4
Set @strBigIndex =convert(varchar(6), @BigIndex)
Set @strSmallIndex =convert(varchar(6), @SmallIndex)

Select @SQL = 'Update [Holistic].[dbo].[4WeekWindowSubtract] set [' + @strBigIndex + ']' = (Select [' + @strBigIndex + ']' - [' + @strSmallIndex + ']' from [Holistic].[dbo].[4WeekWindowAggregation] where [Holistic].[dbo].[4WeekWindowSubtract].[customerID]=[Holistic].[dbo].[4WeekWindowAggregation].[customerID])'
exec(@sql)
Set @BigIndex=@BigIndex+1
end

--For each customer, what has been the worst drop?

select * into #temp
from [Holistic].dbo.[4WeekWindowSubtract]

Declare @Columns as Varchar(max)
Set @Columns=''

select @Columns = @Columns + ',[' + name + ']'
from tempdb..syscolumns
where
id=object_id('tempdb..#temp')
and name <> 'customerID'

Select @Columns = Right(@Columns,len(@Columns)-1)

exec ('insert into [Holistic].[dbo].[4WeekWindowSubtract_Min] (CustomerID, Minvalue) Select customerID,min(val) minval from #temp t
Unpivot(val For data
in (' + @Columns + ') as Upvt
Group by customerID order by customerID')

Drop table #temp

-- For each customer, when was the Dooms Day? 
--*******************************************************************************

declare @SQL varchar(1000),
customerID int,
@strcustomerID varchar(6),
gold int,
silver int,
dateindex date,
doomsDay date,
dateindex2 date,
last date,
columnname varchar(3),
dateID int,
goldchar varchar(4),
@BigIndex int=5,
smallIndex int,
@strBigIndex varchar(6),
@strSmallIndex varchar(6)

Declare CustomerCur cursor for
select customerID
from [Holistic].dbo.[4WeekWindowSubtract_Min]
order by customerID
open CustomerCur
fetch CustomerCur into @CustomerID

while @@FETCH_STATUS=0
begin


select @gold=Minvalue
from [Holistic].[dbo].[4WeekWindowSubtract_Min]
where customerid=@CustomerID

Set @strcustomerID =convert(varchar(6), @customerID)

set @BigIndex=5

While @BigIndex < 103
begin

Set @strBigIndex =convert(varchar(6), @BigIndex)
CREATE TABLE #SubtractData (var int)

SELECT @sql = 'Select [' + @strBigIndex + '] from [Holistic].[dbo].[4WeekWindowSubtract] where CustomerID=' + @strcustomerID

INSERT #SubtractData exec (@sql)
SELECT @silver = var from #SubtractData
DROP TABLE #SubtractData

If (@silver=@gold)
Begin

Select @doomsDay=FirstDayOfWeek
from [Holistic].[dbo].[DateBase]
where DateID=@BigIndex

insert into [Holistic].[dbo].[Dooms] (CustomerID,DoomsIndex,DoomsDay, DoomsValue) values (@CustomerID,@BigIndex,@doomsDay,@gold)

end

Set @BigIndex=@BigIndex+1
end

fetch CustomerCur into @CustomerID
end

close CustomerCur
deallocate CustomerCur
insert into [Holistic].dbo.[importantdays]
(customerID,BizBornWeek, BizStartWeek,DoomsDay,BizEndWeek)
select t1.[CustomerID],t1.[BizBornWeek], t1.[BizStartWeek], t2.[DoomsDay],
t1.[BizEndWeek]
from (SELECT [CustomerID]
    ,[BizBornWeek]
    ,[BizStartWeek]
    ,[BizEndWeek]
FROM [Holistic].[dbo].[CustomerBuinessDuration] ) t1
left join (SELECT [CustomerID]
    ,[DoomsDay]
FROM [Holistic].[dbo].[Dooms] )t2
on t1.customerID=t2.customerid
order by t1.CustomerID asc

--Use Fink & Gandhi’s (Carnegie Mellon) time series compression
-- algorithm to find the first right important or strict important
--maximum before the worst drop (i.e. the outset of drop)

Use [Holistic]
go
declare @customerID int,
@rowID int,
@BizStartWeek date,
@DoomsDay date,
@FinkGandhi date,
@i int,
@b int,
@left int,
@right int,
@n int,
@a_i_plus_one float,
@a_i float,
@a_left float,
@a_right float,
@distance float
Declare RowCur cursor for
select RowID
from [Holistic].dbo.ImportantDays where
Doomsday is not NULL order by rowID
open rowCur
fetch rowCur into @rowID

while @@FETCH_STATUS=0
begin

select @customerID=t0.customerID,
@BizStartWeek=t0.BizStarWeek,
@DoomsDay=t0.DoomsDay
from dbo.ImportantDays t0
where t0.RowID=@RowID

delete from dbo.TempTable

DBCC CHECKIDENT('Holistic.dbo.TempTable', RESEED, 0)

Insert into dbo.TempTable
(FirstDayOfWeek,servicevolume)
select
dbo.DateBase.firstdayofweek,
coalesce(ss.Volume,0)
from dbo.DateBase
left outer join
(select * from dbo.HolisticVolumeIndexed
where CustomerID=@customerID and
FirstDayOfWeek between @BizStartWeek and @DoomsDay) ss
on dbo.DateBase.firstdayofweek=ss.firstdayofweek

where dbo.DateBase.firstdayofweek between @BizStartWeek and @DoomsDay

order by FirstDayOfWeek desc

select @n=max(ID) from dbo.tempTable

set @i=1
set @left=1
set @right=1

select @a_i_plus_one=servicevolume from dbo.TempTable where ID=2
```
select @a_left=servicevolume from dbo.TempTable where ID=1

If (@a_i_plus_one=0 and @a_left=0)
begin
set @distance=0
end
else
begin
Set @distance=ABS(@a_i_plus_one-@a_left)/(@a_i_plus_one+@a_left)
end

While (@i<n AND ((@a_i_plus_one>@a_left) OR ( @distance<1/5)))
Begin
Set @i=@i+1
select @a_i=servicevolume from dbo.TempTable where ID=@i
if @a_left<@a_i
begin
set @left=@i
select @a_left=servicevolume from dbo.TempTable where ID=@left
end
Set @b=@i+1
select @a_i_plus_one=servicevolume from dbo.TempTable where ID=@b
If (@a_i_plus_one=0 and @a_left=0)
begin
set @distance=0
end
else
begin
Set @distance=ABS(@a_i_plus_one-@a_left)/(@a_i_plus_one+@a_left)
end
end
Select @FinkGandhi=firstdayofweek from dbo.TempTable
where ID=@left
```
Update dbo.ImportantDays set FinkGandhi = @FinkGandhi where RowID = @rowID

fetch RowCur into @rowID
end

close rowCur
deallocate rowCur

-**-------------------------------------------------------------**
-**----------------------------------------------------------------**
APPENDIX B: MATCHED SAMPLING ETL

---The churners:nonchurners ratio in the predictive dataset is 1:5---

Declare @customerID int,
@BizBornWeek date,
@ChurnDate date,
@EpisodeLength int

Declare CustomerCur cursor for
SELECT customerID
FROM [Predictive].dbo.predictivechurners
order by episodeLength desc--Why “order by descending?” :) open CustomerCur
fetch CustomerCur into @CustomerID
while @@FETCH_STATUS=0

begin
SELECT
    @BizBornWeek= [BizBornWeek],
    @ChurnDate= [ChurnDate],
    @EpisodeLength= [EpisodeLength]
FROM [Predictive].dbo.predictivechurners
where customerID= @customerID

insert into [Predictive].dbo.MotherDataSet([CustomerID]
    ,[BizBornWeek]
    ,[ChurnDate]
    ,[EpisodeLength]
    ,[Churn])
values
(@CustomerID,
@BizBornWeek,
@ChurnDate)
insert into [Predictive].dbo.MotherDataSet([CustomerID],
[BizBornWeek],
[ChurnDate],
[EpisodeLength],
[Churn])
select top 5 [CustomerID],
@BizBornWeek,
@ChurnDate,
@EpisodeLength,
0
from [Predictive].dbo.predictivenonchurners
where bizbornweek<=@BizBornWeek
and
customerID not in
(select customerID from [Predictive].dbo.MotherDataSet)
order by NEWID()

fetch CustomerCur into @CustomerID
end

close CustomerCur
deallocate CustomerCur
APPENDIX C: ETL FOR COUNTING THE TIMES THE HEURISTICS HOLDS IN
THE WHOLE EPISODE WITH RESPECT TO SQI1

--*************************************************
--Counting the End Pain Frequency
--with respect to SQI1
--*************************************************

Declare @customerID int,
@BizBornWeek date,
@Start date,
@Maxpain int,
@BiasCount int,
@churn bit,
@RecentPainWeeks float,
@RecentServiceWeeks float,
@PriorPainWeeks float,
@PriorServiceWeeks float,
@dateIndex date,
@ChurnDate date,
@Last6WeeksBias bit

Declare CustomerCur cursor for
SELECT customerID
FROM [descriptive2].[dbo].[DescriptiveDataSet]
open CustomerCur
fetch CustomerCur into @CustomerID
while @@FETCH_STATUS=0

begin
set @BiasCount=0
set @RecentPainWeeks=0
set @Last6WeeksBias=0

select @BizBornWeek=BizBornWeek,
@ChurnDate=ChurnDate,
@churn=churn
from [descriptive2].[dbo].[DescriptiveDataSet]
where
CustomerID=@customerID

Set @dateIndex=DATEADD(ww,24,@BizBornWeek)
--24 is the minimum length for our base period...

Set @Start=@dateIndex

while @dateIndex<=DATEADD(ww,-5,@ChurnDate)
--our six-week sliding window...

Begin

Select @RecentPainWeeks=COUNT(*)
from pain.dbo.SQI1Pain
where
CustomerID=@customerID and
FirstDayOfWeek between
@dateIndex and DATEADD(ww,5,@dateIndex)
and OverallPain<>0

if (@RecentPainWeeks>0)
begin
Set @BiasCount=@BiasCount+1

If (@dateIndex=DATEADD(ww,-5,@ChurnDate))
--see if the bias holds in the last six weeks...

Begin
Set @Last6WeeksBias=1
End
End

set @dateIndex=DATEADD(ww,1,@dateindex)
end

insert into descriptive2.dbo. DR_EndPain_SQI1
(CustomerID,Churn,BiasCount,InvestigatedWeeks,Last6WeeksBias)
values
(customerID, churn, @BiasCount, datediff(ww, @start, @churndate) + 1, @Last6WeeksBias)
fetch CustomerCur into @CustomerID
end

close CustomerCur
deallocate CustomerCur

DECLARE @customerID INT,
BizBornWeek DATE,
Start DATE,
Maxpain INT,
BiasCount INT,
churn BIT,
RecentTotalPain FLOAT,
RecentTotalServiceVolume FLOAT,
PriorTotalPain FLOAT,
PriorTotalServiceVolume FLOAT,
dateIndex DATE,
ChurnDate DATE,
Last6WeeksBias BIT

DECLARE CustomerCur CURSOR FOR
SELECT customerID FROM [descriptive2].[dbo].[DescriptiveDataSet]
on open CustomerCur
fetch CustomerCur into @CustomerID
while @@FETCH_STATUS=0
begin
set @BiasCount=0
set @RecentTotalPain=0
set @RecentTotalServiceVolume=0
set @PriorTotalPain=0
set @PriorTotalServiceVolume=0
set @Last6WeeksBias=0
```sql
select @BizBornWeek=BizBornWeek,
@ChurnDate=ChurnDate,
@churn=churn
from ![descriptive2].[dbo].[DescriptiveDataSet]
where CustomerID=@customerID

Set @dateIndex=DATEADD(ww,24,@BizBornWeek)
--24 is the minimum length for our base period...

Set @Start=@dateIndex

while @dateIndex<=DATEADD(ww,-5,@ChurnDate)
--our six-week sliding window...

Begin

Select @RecentTotalPain=sum(overallpain)
from pain.dbo.SQII1Pain where
CustomerID=@customerID and
FirstDayOfWeek between
@dateIndex and DATEADD(ww,5,@dateIndex)

Select @RecentTotalServiceVolume=sum(Volume)
from ![Final-Eyeballed].[dbo].[ServiceVolumeIndexed] where
CustomerID=@customerID and FirstDayOfWeek between
@dateIndex and DATEADD(ww,5,@dateIndex)

Select @PriorTotalPain=sum(overallpain)
from pain.dbo.SQII1Pain where
CustomerID=@customerID and
FirstDayOfWeek between
@BizBornWeek and DATEADD(ww,-1,@dateIndex)

Select @PriorTotalServiceVolume=sum(volume)
from ![Final-Eyeballed].[dbo].[ServiceVolumeIndexed] where
CustomerID=@customerID and FirstDayOfWeek between @BizBornWeek
and DATEADD(ww,-1,@dateIndex)
```
if --No worries about divide by zero! Why? :) 
((@RecentTotalPain/@RecentTotalServiceVolume)>
(@priorTotalPain/ @PriorTotalServiceVolume))

begin
Set @BiasCount=@BiasCount+1
If (@dateIndex=DATEADD(ww,-5,@ChurnDate))
--See if the bias holds in the last six weeks...
Begin
Set @Last6WeeksBias=1
End

End

set @dateIndex=DATEADD(ww,1,@dateindex)
end

insert into descriptive2.dbo. DR_ExtensionalEndPain_SQI1_Pain
(CustomerID,Churn,BiasCount,InvestigatedWeeks,Last6WeeksBias) values
(@customerID,@churn,@BiasCount,
datediff(ww,@start,@churndate)+1,@Last6WeeksBias)

fetch CustomerCur into @CustomerID
end

close CustomerCur
deallocate CustomerCur

-**********************
--Counting the Peak Pain Frequency
--with respect to SQI1
-**********************

Declare @customerID int,
@BizBornWeek date,
@Start date,
@BiasCount int,
@churn bit,
@RecentMaxPain float,
@PriorMaxPain float,
@dateIndex date,
@ChurnDate date,
@Last6WeeksBias bit

Declare CustomerCur cursor for
SELECT customerID
FROM [descriptive2].[dbo].[DescriptiveDataSet]
open CustomerCur
fetch CustomerCur into @CustomerID
while @FETCH_STATUS=0

begin
set @BiasCount=0
set @RecentMaxPain=0
set @PriorMaxPain=0
set @Last6WeeksBias=0

select @BizBornWeek=BizBornWeek,
@ChurnDate=ChurnDate,
@churn=churn
from
[descriptive2].[dbo].[DescriptiveDataSet]
where CustomerID=@customerID

Set @dateIndex=DATEADD(ww,24,@BizBornWeek)--Need this for our base...

Set @Start=@dateIndex

while @dateIndex<=DATEADD(ww,-5,@ChurnDate) --Our sliding window

Begin

Select @RecentMaxPain=Max(overallpainRate)
from pain.dbo.SQI1Pain
where
CustomerID=@customerID
and
FirstDayOfWeek between @dateIndex and DATEADD(ww,5,@dateIndex)

Select @PriorMaxPain=Max(overallpainRate)
from pain.dbo.SQI1Pain
where
CustomerID=@customerID and
FirstDayOfWeek between @BizBornWeek
and DATEADD(ww,-1,@dateIndex)
if (@RecentMaxPain>@PriorMaxPain)
begin
Set @BiasCount=@BiasCount+1
end

If (@dateIndex=DATEADD(ww,-5,@ChurnDate))
--Happened just before the end of episode?
Begin
Set @Last6WeeksBias=1
End
End

set @dateIndex=DATEADD(ww,1,@dateindex)
end

insert into descriptive2.dbo.
DR_PeakPain_SQI1_PainRate(CustomerID,Churn,BiasCount,InvestigatedWeeks ,Last6WeeksBias)
values (@customerID,@churn,@BiasCount, datediff(ww,@start,@churndate)+1,@Last6WeeksBias)

fetch CustomerCur into @CustomerID
end

close CustomerCur
deallocate CustomerCur

--*******************************************************************************
--Counting the Availability Heuristic Frequency
--with Pain Incidents and respect to SQI1
--*******************************************************************************

Declare @customerID int,
@BizBornWeek date,
@Start date,
@Maxpain int,
@BiasCount int,
@churn bit,
@RecentTotalPainIncident float,
@RecentServiceWeeks float,
Declare CustomerCur cursor for
SELECT customerID
FROM
[descriptive2].[dbo].[DescriptiveDataSet]
open CustomerCur
fetch CustomerCur into @CustomerID
while @@FETCH_STATUS=0
begin
set @BiasCount=0
set @RecentTotalPainIncident=0
set @RecentServiceWeeks=0
set @PriorTotalPainIncident=0
set @PriorServiceWeeks=0
set @Last6WeeksBias=0

select @BizBornWeek=BizBornWeek,
@ChurnDate=ChurnDate,
@churn=churn
from
[descriptive2].[dbo].[DescriptiveDataSet]
where CustomerID=@customerID
Set @dateIndex=DATEADD(ww,24,@BizBornWeek)--24 is the minimum length of prior!
Set @Start=@dateIndex
while @dateIndex<=DATEADD(ww,-5,@ChurnDate)
Begin
Select @RecentTotalPainIncident=sum([OverallPain])
from pain.dbo.SQI1Pain
where CustomerID=@customerID and FirstDayOfWeek between @dateIndex and DATEADD(ww,5,@dateIndex)
Select @RecentServiceWeeks=COUNT(*)
from [Final-Eyeballed].[dbo].[ServiceVolumeIndexed]
where CustomerID=@customerID
and FirstDayOfWeek between @dateIndex and DATEADD(ww,5,@dateIndex)
Select @PriorTotalPainIncident=sum([OverallPain])
from pain.dbo.SQI1Pain
where
CustomerID=@customerID and
FirstDayOfWeek between @BizBornWeek and DATEADD(ww,-1,@dateIndex)
Select @PriorServiceWeeks=COUNT(*) from [Final-Eyeballed].[dbo].[ServiceVolumeIndexed]
where
CustomerID=@customerID and FirstDayOfWeek between @BizBornWeek and DATEADD(ww,-1,@dateIndex)

If (@RecentServiceWeeks<>0) and (@PriorServiceWeeks<>0))
begin
if ((@RecentTotalPainIncident/@RecentServiceWeeks)>(@PriorTotalPainIncident/@PriorServiceWeeks))
begin
Set @BiasCount=@BiasCount+1

If (@dateIndex=DATEADD(ww,-5,@ChurnDate))
Begin
Set @Last6WeeksBias=1
End
End
End

set @dateIndex=DATEADD(ww,1,@dateindex)
end

insert into descriptive2.dbo.
DR_AvailabilityHeuristic_SQI1_PainIncident
(CustomerID,Churn,BiasCount,InvestigatedWeeks,Last6WeeksBias)
values
(@customerID,@churn,@BiasCount,
datediff(ww,@start,@churndate)+1,@Last6WeeksBias)

fetch CustomerCur into @CustomerID
end
close CustomerCur
deallocate CustomerCur

---*****************************************
-- Counting the Availability Heuristic Frequency
-- with Pain Weeks and with respect to SQI1
---*****************************************

Declare @customerID int,
@BizBornWeek date,
@Start date,
@Maxpain int,
@BiasCount int,
@churn bit,
@RecentPainWeeks float,
@RecentServiceWeeks float,
@PriorPainWeeks float,
@PriorServiceWeeks float,
@dateIndex date,
@ChurnDate date,
@Last6WeeksBias bit

Declare CustomerCur cursor for
SELECT customerID
FROM [descriptive2].[dbo].[DescriptiveDataSet]
open CustomerCur
fetch CustomerCur into @CustomerID
while @@FETCH_STATUS=0

begin
set @BiasCount=0
set @RecentPainWeeks=0
set @RecentServiceWeeks=0
set @PriorPainWeeks=0
set @PriorServiceWeeks=0
set @Last6WeeksBias=0

select @BizBornWeek=BizBornWeek,
@ChurnDate=ChurnDate,
@churn=churn
from [descriptive2].[dbo].[DescriptiveDataSet]
where CustomerID=@customerID

Set @dateIndex=DATEADD(ww,24,@BizBornWeek)-- 24 is the minimum base
Set @Start=@dateIndex

while @dateIndex<=DATEADD(ww,-5,@ChurnDate)

Begin
Select @RecentPainWeeks=COUNT(*)
from pain.dbo.SQII1Pain
where CustomerID=@customerID
and FirstDayOfWeek between @dateIndex and DATEADD(ww,5,@dateIndex)
and OverallPain<>0

Select @RecentServiceWeeks=COUNT(*)
from [Final-Eyeballed].[dbo].[ServiceVolumeIndexed]
where CustomerID=@customerID and
FirstDayOfWeek between @dateIndex and DATEADD(ww,5,@dateIndex)

Select @PriorPainWeeks=COUNT(*)
from pain.dbo.SQII1Pain
where CustomerID=@customerID and
FirstDayOfWeek between @BizBornWeek and DATEADD(ww,-1,@dateIndex)
and OverallPain<>0

Select @PriorServiceWeeks=COUNT(*) from
[Final-Eyeballed].[dbo].[ServiceVolumeIndexed]
where CustomerID=@customerID and
FirstDayOfWeek between @BizBornWeek and DATEADD(ww,-1,@dateIndex)

If (@RecentServiceWeeks<>0) and (@PriorServiceWeeks<>0)
Begin
if (@RecentPainWeeks/@RecentServiceWeeks)>(@PriorPainWeeks/@PriorServiceWeeks)
begin
Set @BiasCount=@BiasCount+1
If (@dateIndex=DATEADD(ww,-5,@ChurnDate))
Begin
Set @Last6WeeksBias=1
End
End
End

set @dateIndex=DATEADD(WW,1,@dateindex)
end

insert into descriptive2.dbo.DR_AvailabilityHeuristic_SQI1_PainWeek (CustomerID,Churn,BiasCount,InvestigatedWeeks,Last6WeeksBias) values (@customerID,@churn,@BiasCount,datediff(ww,@start,@churndate)+1,@Last6WeeksBias)

fetch CustomerCur into @CustomerID
end

close CustomerCur
deallocate CustomerCur

--******************************************************************************
--COUNTING THE AVAILABILITY HEURISTIC FREQUENCY
--WITH PAIN WEEKS AND WITH RESPECT TO ALL SQIs
--******************************************************************************

Declare @customerID int,
@BizBornWeek date,
@Start date,
@Maxpain int,
@BiasCount int,
@churn bit,
@RecentPainWeeks float,
@RecentServiceWeeks float,
@PriorPainWeeks float,
@PriorServiceWeeks float,
@dateIndex date,
@ChurnDate date,
@Last6WeeksBias bit

Declare CustomerCur cursor for
SELECT customerID
FROM [descriptive2].[dbo].[DescriptiveDataSet]
open CustomerCur
fetch CustomerCur into @CustomerID
while @@FETCH_STATUS=0

begin
set @BiasCount=0
set @RecentPainWeeks=0
set @RecentServiceWeeks=0
set @PriorPainWeeks=0
set @PriorServiceWeeks=0
set @Last6WeeksBias=0

select @BizBornWeek=BizBornWeek,
      @ChurnDate=ChurnDate,
      @churn=churn
from [descriptive2].[dbo].[DescriptiveDataSet]
where CustomerID=@CustomerID

Set @dateIndex=DATEADD(ww,24,@BizBornWeek)
--24 is the minimum base...

Set @Start=@dateIndex

while @dateIndex<=DATEADD(ww,-5,@ChurnDate)
Begin

Select @RecentPainWeeks=COUNT(*)
from pain.dbo.WeightedPainByEXPERT
--The count from this table encompass
--all different types of service pains...
where CustomerID=@customerID
and FirstDayOfWeek between @dateIndex and DATEADD(ww,5,@dateIndex) and OverallPain<>0

Select @RecentServiceWeeks=COUNT(*)
from [Final-Eyeballed].[dbo].[ServiceVolumeIndexed]
where CustomerID=@customerID and
FirstDayOfWeek between @dateIndex and DATEADD(ww,5,@dateIndex)

Select @PriorPainWeeks=COUNT(*)
from pain.dbo.WeightedPainByEXPERT
where CustomerID=@customerID and
FirstDayOfWeek between @BizBornWeek and DATEADD(ww,-1,@dateIndex)
and OverallPain<>0

Select @PriorServiceWeeks=COUNT(*)
from [Final-Eyeballed].[dbo].[ServiceVolumeIndexed]
where CustomerID=@customerID
and FirstDayOfWeek between @BizBornWeek and DATEADD(ww,-1,@dateIndex)

If (@RecentServiceWeeks<>0 and @PriorServiceWeeks<>0)
begin
  if (@RecentPainWeeks/@RecentServiceWeeks)>
     (@PriorPainWeeks/@PriorServiceWeeks)
  begin
    Set @BiasCount=@BiasCount+1
  end
  If (@dateIndex=DATEADD(ww,-5,@ChurnDate))
  Begin
    Set @Last6WeeksBias=1
  End
End
End

set @dateIndex=DATEADD(ww,1,@dateindex)
end

insert into descriptive2.dbo.
  DR_AvailabilityHeuristic_AllPains_PainWeek
  (CustomerID,Churn,BiasCount,InvestigatedWeeks,Last6WeeksBias)
  values
  (@customerID,@churn,@BiasCount,datediff(ww,@start,@churndate)+1,@Last6WeeksBias)

fetch CustomerCur into @CustomerID
end

close CustomerCur
deallocate CustomerCur