Towards Exploring Factors Affecting Decision Outcome and Lead-time in Large-Scale Requirements Engineering

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SUMMARY

Lead-time is crucial for decision-making in market-driven requirements engineering. Lead-time efficiency allows software companies to focus their resources on the most profitable functionality, and enables to remain competitive on the fast-changing software market. Achieving and sustaining low decision lead-time and the resulting high decision efficiency, requires better understanding of factors that may affect both decision lead-time and outcome. In order to identify possible factors, we conducted an exploratory two-stage case study that combines the statistical analysis of seven possible relationships among decision characteristics at a large company with a survey among industry participants. Our results show that the number of products affected by a decision increases the time needed to make a decision. Practitioners should take this aspect into consideration when planning for efficient decision-making and possibly reducing the complexity of decisions. Our results also show that when a change request originates from an important customer, the request is more quickly accepted. The result provides input into the discussion if a large company should only focus on few yet large customers and disregard a significantly large group of small customers. Our results provide valuable insights for both researchers, who can use them to plan research of decision-making processes and methods, and for practitioners, who can use them to optimize their decision-making processes.

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KEY WORDS: Requirements Engineering; Decision Making; Market-Driven Requirements Engineering; Software Product Lines
1. INTRODUCTION

Requirements Engineering (RE) addresses the critical problem of designing the right software for the customer (Aurum and Wohlin 2005). In Market–Driven Requirements Engineering (MDRE), the content of the product has to be aligned with targeted market needs to create a profitable software product (Regnell and Brinkkemper 2005). For large MDRE projects, with thousands of continuously arriving (Karlsson et al 2007a) potential requirements, deciding which requirements should be implemented is far from trivial. Moreover, customer needs keep evolving and cause changes to requirements. Promptly analysing and deciding upon these changes is crucial for staying competitive in the software market (Jonsson and Lindvall 2005).

Large companies often use the software platform concept, also known as Software Product Lines (SPL) (Pohl et al 2005). SPL help to decrease the cost and to increase the ability to provide an individualized software product. Moreover, SPL allow software development organizations to reuse a common technology base to meet customers needs. However, the cost for this greater degree of reuse and increased productivity is increased complexity of coexisting product variants and more complex decision–making.

The requirements selection process is a complex decision problem that introduces several challenges, e.g. shifting goals, time stress (Alenljung and Persson 2008b) and uncertain estimates (Karlsson and Ryan 1997) just to name a few. To effectively improve RE decision–making, more effort should be dedicated towards decision–making aspects identification (Alenljung and Persson 2008b, Natt och Dag et al 2005). In particular, it is important to explore additional factors influencing both the time needed to make the decision (also called the decision lead–time) as well as the outcome of the decision process. The knowledge of these factors and their impact could guide improvement proposals for more optimal requirements decision–making.

In this paper, we report upon a two-stage exploratory case study designed with the aim of identifying which characteristics of change requests, i.e. number of products, release number, type of customer, may influence the decision lead–time and the decision outcome. In the first stage, a decision log containing over 1000 decisions was statistically analyzed to uncover possible relationships between factors affecting the decision lead–time and the decision outcome. Next, a survey among industry participants was conducted to further explore possible factors and to evaluate the statistical analysis results.
The decision lead–time is in this context defined as the time required to analyze the impact of a decision. The decision outcome is in this context defined as a specific outcome of the decision process, namely acceptance or rejection. For brevity, we use decision outcome throughout the paper.

The main goals for the paper are threefold: (1) to explore possible factors that may influence the decision lead–time, (2) to investigate the possible factors that may influence the decision outcome and (3) to investigate if the decision lead–time affects the decision outcome. Partial results from this study have previously been published as a workshop publication in 2010 (Kabbedijk et al 2010). This paper extends our previous work by: (1) validating the results of the decision log analysis in a survey, (2) extending the analysis of the results regarding factors that affect the decision lead-time and the relationship between the decision lead-time and the decision outcome, (3) extending the analysis of related work, (4) extending the interpretation of the results in the light of the related work.

The paper is structured as follows. Related work is discussed in Section 2, followed by a description of the case study company in Section 3. Our research design and research questions are outlined in Section 4. Next, we present the results of the statistical analysis of the decision logs and the survey in Section 5. We conclude the paper and present the future work in Section 8.

2. RELATED WORK

2.1. Decision Making in RE

Decision making is an important aspect of requirements engineering (Alenljung and Persson 2008b, Aurum and Wohlin 2003, Evans et al 1997) and significantly impacts requirements management. As stated by DeGregorio (1999), requirements management is not possible without decision management. One of the decision-intensive phases of requirements management is change impact analysis (Jonsson and Lindvall 2005). Therefore, understanding the nature of the decisions made in the RE process is necessary for improving the process (Aurum and Wohlin 2003).

Defining the scope of a product by selecting the right features is a known risk in project management (Boehm 1989) and requirements changes are among the top risks in software engineering (Boehm 1989). Further, adding functionality during the course of the project also negatively impacts project goals (DeMarco and Lister 2003). Despite an increasing awareness for supporting RE decision–making, more research is needed in this area (Ngo-The and Ruhe 2005).
The requirements engineering process is a decision rich activity for which decisions range from the organization level to the project level (Aurum and Wohlin 2003, Ngo-The and Ruhe 2005). Moreover, since RE decision–making is a knowledge–intensive activity that is performed in natural settings, it has to deal with the difficulties such as shifting, ill–defined or competing goals and values (Klein et al 1995) or multi-objective decision problems (Veerappa and Letier 2011). Moreover, power and politics are also impacting decision–making processes in requirements engineering (Milne and Maiden 2012). As a result, the risk of making inappropriate decisions is high and the consequences of wrong decisions can be serious.

RE decisions are often semi–structured or unstructured and made only once, hindering the evaluations of the decision outcomes (Ngo-The and Ruhe 2005). Moreover, Strigini (1996) stressed that important decisions in software industry depend on subjective judgments and suggested using quantitative methods to increase objectivity. Thus, empirical investigations of the factors that affect decision outcomes are important as they could contribute to more continuous, controllable and structured requirements engineering decision–making. The empirically obtained knowledge of potential factors that affect decisions could help decision makers in better planning of decisions and earlier identification of possible process bottlenecks.

2.2. Modeling decision making in SE and RE

Several researchers have looked into modeling decision–making in software and requirements engineering. Ashrafi (1998) proposed a decision–making model that addresses various software quality aspects. Rolland et al. (1995) proposed a decision–making meta–model for requirements engineering process that captures both how and why the requirements engineering activities are performed. Wild et al. (1994) modeled the software development process as a set of problem solving activities (decisions) while Veerappa and Letier (2011) focused on understanding clusters of optimal solutions in multi-objective decision problems. Kukreja et al. (2013) proposed a requirements prioritization method based on vector space model and computation from multiple-criteria analytics.

Sellier et al. (2008) focused on modeling inter-dependencies of requirements selections for software product lines. Liu and Lin (2008) proposed a system to support decision-making during requirements elicitation. Finally, Alenljung and Persson (2008a) proposed a method for evaluating decision-supporting capabilities of requirements engineering tools.

Ruhe (2005) modeled release planning decisions by combining computational knowledge intelligence and experience of decision makers or by using linear programming (Ruhe 2009).
Al-Emran et al. (2010) suggested using robustness analysis to support requirements engineering decision-making. van den Akker et al. (2008) used integral linear programming to find an optimal set of requirements within the given resource constraints that can maximize the revenue. Chen et al. (2010) focused on time scheduling aspect of release planning. Regnell and Kuchcinski used constraint programming (Regnell and Kuchcinski 2011) to model release planning decision-making while Egyed et al. (2006) proposed using constraints programming for reducing the number of possible software design decisions. Karlsson (1997) promoted a cost–value approach for prioritizing requirements which was later experimentally compared to other prioritization techniques (Karlsson et al 2007b). Ruhe (2009) covered supporting product release decisions on various levels by modeling the release planning criteria and constraints. The mentioned methods mainly focus on the task of reducing the number of possible decision or assigning features to releases according to given criteria, while this study focuses on understanding the factors that may affect decision lead-times and outcomes.

2.3. Challenges in RE decision making

Among the challenges in RE decision–making Alenljung et al. (2008b) listed: ill–structured problems, uncertain environments, shifting goals, action and feedback loops, time stress, high stakes, multiple player situations and organizational goals and norms. Ngo-The and Ruhe (2005) argued that requirements decisions are hard because of the incompleteness of the available information and any notion of strict optimality is not appropriate in this context. Karlsson et al. (2007a) listed release planning based on uncertain estimates as one of the challenges in MDRE that is related to RE decision–making. Another challenging aspect of decision–making, mentioned by Fogelstrom et al. (2009a), is finding the right balance between the commercial requirements selected over internal quality requirements (also mentioned by Karlsson et al. (2007a)). Furthermore, requirements prioritization (Karlsson and Ryan 1997) was recognized as challenging because of, e.g. conflicting priorities between stakeholders (Berander and Andrews 2005), complex dependencies between requirements (Cleland-Huang et al 2005) or multi-objective decision problems (Veerappa and Letier 2011). MacAvoy et al. (2009) discovered that the high level of empowerment of a cohesive agile software development team may negatively impact decision–making. Finally, several researchers stressed the need for empirical studies in RE decision–making process to create a coherent body of knowledge in RE decision–making and to improve requirements engineering (Alenljung and Persson 2008b, Aurum and Wohlin 2003, Berander and Andrews 2005).
2.4. Empirical studies in RE decision making

Despite the above mentioned need for more empirical studies and several reported studies that outlined challenges in requirements engineering decision–making (see Section 2.3), the number of publications that empirically investigate factors affecting decision–making in requirements engineering is still low. Among the reported studies, Wohlin and Aurum (2005) investigated the criteria used in the requirements selection process for a project or release and reported that business–oriented and management–oriented criteria are more important than technical concerns. Wnuk et al. (2009a) investigated the reasons for excluding features from the project’s scope reporting that the stakeholder business decision is the dominant reasons for feature exclusions. Fogelstrom et al. (2009b) investigated whether product managers take more risks during requirements selection. Barney et al. (2008) reported that the client and market base of the software product are the dominant factors that affect the decision to implement specific requirements. They stressed that factors such as maturity of the product, the marketplace in which it exists and the available development tools and methods also influence the decision of whether or not include requirements in a software product. To the best of our knowledge, no study had yet attempted to investigate factors that affect both decision lead–times and decision outcomes.

2.5. Organisational perspective of decision–making

Khatri (2000) discussed the intuition’s role in decision–making whereas Messerschmitt and Szyperski (2004) discussed the “marketplace issues” that may affect software project planning and decision–making. Hogarth (1975) proposed a relationship function between the decision time and the task complexity. Saliu and Ruhe (2005) suggested that there is a relationship between decision outcomes and release planning. A similar relationship was suggested by Bagnall (2001) but, as in Ruhe and Saliu (2005), the relationship wasn’t named. Zur and Breznitz (1981) suggested a relationship between the time pressure, people’s experience and the risks of their choice behaviors. Hallowell (1996) suggested a relationship among customer satisfaction, loyalty and profitability. McAvoy and Butler (2009) observed factors contributing to ineffective decision–making within Agile development projects, mentioning that group interaction shapes decision–making and outcomes and that team cohesion could be a source of dysfunctional decision–making. However, the mentioned relationships were not empirically investigated in a large-scale MDRE context and especially in relation to decision lead–times and decision outcomes. Gaining this knowledge could add to improvements in business practice or in researchers’ understanding of
the phenomenon which in turn may lead to more efficient decision–making, an important factor to remain competitive on the market (Jonsson and Lindvall 2005).

3. CASE COMPANY DESCRIPTION

Table I. The demographic information related to the case study.

<table>
<thead>
<tr>
<th>Type of company</th>
<th>Developer embedded systems on the global market</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of employees</td>
<td>More than 4000</td>
</tr>
<tr>
<td>Major project</td>
<td>A platform project with a two year lead-time</td>
</tr>
<tr>
<td>Minor projects</td>
<td>Further platform releases usually focused on the platform’s adaptations for different products</td>
</tr>
<tr>
<td>Decision entity</td>
<td>A feature, defined as a group of requirements that constitute new functionality enhancements to the platform upon which market value and implementation cost can be estimated.</td>
</tr>
<tr>
<td>Number of features in a typical project</td>
<td>A typical major project has several hundreds of features, up to one thousand. A typical minor project has less than 100 features.</td>
</tr>
<tr>
<td>The scope management process</td>
<td>The scope is maintained in a document called a feature list, that is updated each week after a meeting of the change control board.</td>
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</tbody>
</table>

This paper uses the analysis of work artifacts technique (Lethbridge et al 2005) to study the record of decisions made in an industrial project at the large company using the Software Product Line (SPL) approach (Pohl et al 2005). The demographic information is summarized in Table I. The company operates globally selling embedded systems and has more than 4000 employees. The core of the software part of embedded systems is called a platform and corresponds to the common code base of the SPL (Pohl et al 2005). There are several consecutive releases of the platform in which each of them is a basis for one or more products that reuse the platform’s functionality and qualities. A major platform release has approximately a two year lead–time from start to launch, and is focused on functionality growth and quality enhancements for a product portfolio. Minor platform releases are usually focused on the platform’s adaptations to the different products that will be later launched. In this study, we analyzed one of the major platform release projects. The company took precautions that the project members (including management) are optimally selected and remains stable during the project in order to avoid destabilizing the project and decision–making.

The stage–gate model with several increments (Cooper 1990) is used by the company. The scope of each platform project is constantly changing during this process, from the initial road-map extraction which is a basics for creating high level features to the final milestone of the requirements management process after which the development phase starts. There are four milestones before the implementation starts and three during the implementation and maintenance. In the first milestone of
the requirements phase (called M1) the long-term roadmap is extracted to formulate a set of features. Next, at milestone M2, the features are redefined to requirements and handed over to the design teams to prepare software design. At milestone M3, the effort estimates are produced based on the prepared requirements and design documents. Finally, at the last requirements milestone (M4), the implementation plans based upon ready requirements and design deliverables are produced. In the first phase of the development (at milestone M5), the requirements are developed and delivered to the common platform. At the next milestone (M6), code stability is ensured and preparations to the customer testing and being held. Finally, at the last stage (milestone M7), customer-reported issues are addressed and suggestions are taken into consideration. The software is ready to be released on the market.

The case company utilizes the concept of a *feature* as an entity for making scoping decision. A *feature* is defined as a group of requirements that constitute new functionality enhancements to the platform upon which market value and implementation cost can be estimated. The project decision makers consider both internally issued features and features from external customers. Change requests to these features are performed constantly by stakeholders from inside and outside the company. The change control system is used in order to capture, track and assess the impact of changes (Kitchenham *et al* 1999, Leffingwell and Widrig 2003). The scope of each project is maintained in a document called the feature list, that is updated each week after a meeting of the Change Control Board (CCB). The CCB consists of product and platform managers, complemented with other project stakeholders to a total of about 20 members. The CCB has a champion who is responsible for leading the CCB meetings (Leffingwell and Widrig 2003). The role of the CCB is to decide upon adding or removing features according to issued change requests. The decision process of the CCB is illustrated in Figure 1.

The CCB decision process is depicted in Figure 1. The process is similar to the processes described in the related literature (Jonsson and Lindvall 2005, Kitchenham *et al* 1999, Leffingwell and Widrig 2003). The change requests are high level requests on feature level (regarding new functionality). After a change request is filed, its ambiguity and completeness are analyzed. This analysis is based on the quality gateway model (Natt och Dag *et al* 2001), also called the “firewall” by Leffingwell and Widrig (2003). If the request is ambiguous or incomplete, it is sent back to the submitter to ask for a clarification, otherwise the request is put on the CCB agenda for performing the impact analysis. The impact analysis is performed by the appropriate Technical Groups that elicit and specify high–level requirements for a special technical area and Focus
Groups that design and develop previously defined functionality. During impact analysis, both directly affected requirements and dependent requirements are identified and costs of change and acceptability are assessed (Jonsson and Lindvall 2005, Kotonya and Sommerville 1998). The impact analysis investigations also assess the impact of the proposed change on the software architecture (modularity, coupling and cohesions). The potential cost of a change is also discussed with the Focus Groups. However, these costs were not recorded in the decision log, hindering the analysis of the notion of cost and architectural impact of changes. Each change request has one requirements engineer responsible for driving and facilitating the investigation and for preparing necessary analysis and rationale for the CCB decision–making (Wnuk et al. 2009b).
After the impact analysis, the request is presented at the weekly CCB meeting (step Decide at Meeting in Figure 1). During the CCB meeting, change proposals are reviewed one by one, followed by discussions and clarifications. When the analysis performed by a certain group is not clear enough, extra information can be requested before the final decision is made. If the request is accepted, the change is implemented, else the submitter gets a rejection notification. The CCB neither selects the issues to be discussed (this is done by requirements engineers who coordinate IA investigations) nor follows up detailed tasks that should be executed if a change is accepted (Samalikova et al 2009). All change requests and decisions made about them (including their rationale) are stored in the scope decision log of a project. In this sense, the company follows the advice of Aurum and Wohlin (2003) that the rationale and effects of RE decisions on software product should be tracked in order to support and improve RE activities.

An example of an entry in the decision log is shown in Table II. For reasons of confidentiality, we used fictive data. This decision log comprises a number of attributes like the change submitter and justification, the date that the request has been submitted and decided upon, the products impacted by a change, the release of the platform project impacted by a change, and the markets impacted by a change. The release of the platform project impacted by a change attribute is used to request a certain feature in an earlier release (low release number) or in a later release (high release number). For brevity, we will call this attribute release number throughout the paper. For this paper, we were granted access to an extensive decision log. This log contained 1439 change requests for products planned to be released in 2008.

<table>
<thead>
<tr>
<th>Table II. Decision log entry example</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ID</strong></td>
</tr>
<tr>
<td><strong>Change Request</strong></td>
</tr>
<tr>
<td><strong>Decision Outcome</strong></td>
</tr>
<tr>
<td><strong>Comments</strong></td>
</tr>
<tr>
<td><strong>Description of proposed change</strong></td>
</tr>
<tr>
<td><strong>Justification</strong></td>
</tr>
<tr>
<td><strong>Proposition Area</strong></td>
</tr>
<tr>
<td><strong>Main affected Technical Group</strong></td>
</tr>
<tr>
<td><strong>Affected product</strong></td>
</tr>
<tr>
<td><strong>Affected key customer</strong></td>
</tr>
<tr>
<td><strong>Affected Functional Group</strong></td>
</tr>
<tr>
<td><strong>Submittal Date</strong></td>
</tr>
<tr>
<td><strong>RM tool ID</strong></td>
</tr>
<tr>
<td><strong>Decision Date</strong></td>
</tr>
</tbody>
</table>
4. RESEARCH DESIGN

Since the number of papers that investigate factors influencing RE decision–making is low (see Section 2), our research was mainly exploratory and conducted in order to: (1) identify the main decision characteristics and (2) analyze the relationships between the identified characteristics. After identifying the characteristics, we transformed them to research questions, which can be found in Section 4.1. We ran statistical tests on empirical data to either accept or reject hypotheses and to draw conclusions based on the test results. The results of the statistical analysis were further validated in a survey and interpreted in the light of related studies.

4.1. Research questions

Three research questions are investigated in this paper and are outlined in Table III, complemented with aims. The questions were shaped and inspired by the related literature outlined in Section 2. All three research questions are relationship questions which investigate the relationship between two different phenomena, e.g. does occurrence of one phenomenon correlate with the occurrence of another phenomenon (Easterbrook et al 2008). The questions are further decomposed into hypotheses that were investigated using statistical tests, see Section 5.

<table>
<thead>
<tr>
<th>Research question</th>
<th>Aim</th>
</tr>
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<tbody>
<tr>
<td>RQ1: Which decision characteristics affect the decision lead–time?</td>
<td>To understand which decision characteristics i.e, number of products, release number, type of customer have a significant impact on the decision lead–time</td>
</tr>
<tr>
<td>RQ2: Which decision characteristics affect the decision outcome?</td>
<td>To understand the relation between the decision characteristics and the acceptance or rejection of a decision</td>
</tr>
<tr>
<td>RQ3: Is the decision outcome related to the decision lead–time?</td>
<td>To understand the relation between the acceptance rate and the decision lead–time</td>
</tr>
</tbody>
</table>

The first research question (RQ1) is inspired by Hogarth (1975), who created a function on the relationship between the decision time and the task complexity. Hogarth stated that the amount of time needed to make a decision is an increasing function of the task complexity. Beyond a certain threshold, it is cheaper to make decisions (and face potential costs if they were wrong decisions) than to invest time in understanding their complex nature. This is the tilting point at which the amount of time becomes a decreasing function of the task complexity. In this paper, we empirically
investigated the viewpoint of Hogart (1975) as well as we investigated further factors that may influence the decision lead–time, e.g. the type of the customer and the release number.

The second research question (RQ2) investigates the relationships between the decision characteristics and the decision outcome. This question is partly based on the work of Saliu and Ruhe (2005) and the work of Bagnall et al. (2001) suggesting a relationship between decision outcomes and release planning. However, their work (Bagnall et al 2001, Saliu and Ruhe 2005) didn’t suggest any explicit relationship between setting the requirements release time and the decision outcome. Therefore, RQ2 focuses on investigating if such relationships could be found.

Among other related studies, the paper by Hallowell (1996), suggested a relationship among customer satisfaction, loyalty and profitability. Thus, it is reasonable to assume a possible relationship between the fact that a request is filed by an important customer and its decision outcome. Software companies should keep their customers satisfied and thus they could accept requests of these customers more quickly than internal requests.

Research question RQ2 is also based on the work of Hogarth (1975). Since there is a tilting point in the relationship curve, there is a certain complexity level after which the decision maker decides the errors costs due to a wrong decision are lower than the costs of spending any more time on making the decision. From this point it is logical to state a hypothesis that negative decisions could be made and a relationship between the decision outcome and the number of products affected by a decision could exist.

The last research question (RQ3) is based on the work of Zur (1981) and our previous work (Wnuk et al 2009a). In our previous work (Wnuk et al 2009a), we reported that project management is more eager to accept features in the beginning of a large project and exclude features towards the end of the project due to time pressures and other unexpected difficulties. Rajlich and Bennett (2000) reported that during the late servicing phase of software products, changes are both difficult and expensive and therefore they should be minimized. In a related paper, Zur (1981) claimed a relationship between the time pressure peoples experience and the risks of their choice behavior. Thus, we investigated in this study if longer lead–times impact decision outcomes.

4.2. Research methods

Case study and survey methods were selected for conducting this study. Both methods are considered as relevant for software engineering research (Easterbrook et al 2008, Runeson and Höst 2009). The details of the methods are outlined in the subsections that follow.
4.2.1. Case study Case studies have been recognized as an appropriate method to understand complex social phenomena (Yin 2008) and highly recommended for software engineering research (Runeson and Höst 2009). We used the analysis of electronic databases of work performed technique (Lethbridge et al 2005) for data collection as it is a suitable technique for analyzing large amounts of data. The researchers were granted access to an extensive decision log of all products planned to be released in 2008 containing 1439 change requests. To address the risk of low control over the gathered information quality, the data was validated with one practitioner from the case company and analyzed by two authors of this paper to perform observer triangulation. Based on the decision characteristics (see Section 3), five variables were created for each decision.

1. Lead-Time: the duration between the moment a request was filed to the moment the decision was made by the CCB. The lead–time is measured in week days and not working days, so there could be a small difference in days between two decisions who took the same number of working days to be taken, due to weekends. Figure 2 gives an indication of how the lead–time is distributed. About half of the decisions are made the same day they are requested (686 decisions, 48%), but the 753
requests that are left can take up to 143 days before a decision is made.

2. **Number of Products Affected:** a number between one and fourteen (the total number of product for this software product line) indicating the number of different products for which the requirements would change if the request was accepted. We consider this attribute as a proxy for decision complexity.

3. **Release Number:** a variable strongly related to the release method used within the case company. As described in Section 3, the product line platform of the case company is released in a heartbeat rhythm of one base release and four sequential releases. The release number variable indicates the specific number of the release affected by the change request. The higher the variable, the later the release is in the release heartbeat rhythm of the case company.

4. **Type of Customer:** a nominal variable used to indicate whether a request is filed by an important external customer or is a request coming from inside the company. External customers in this case are large partners of the case company who also help to bring the developed products to the market. Thus, we refer to them as *important external customers.*

5. **Decision Outcome:** a variable of nominal level of measurement indicating whether or not a change request is accepted by the CCB.

4.2.2. **Survey** We conducted a survey among 50 respondents from industry to validate the results from the case study as well as to strengthen the external validity of the study. The survey respondents were mainly working for companies producing product software using the SPL approach. The sample was sourced by sending the invitation to participate in the survey to several mailing lists and LinkedIn groups (for example the LinkedIn group for Software Product Management). The questionnaire was created based on principles described by Kitchenham and Pfleeger (2002). The questionnaire contained a part dedicated to identify the context and background of the respondents, followed by a part focusing on their experiences considering possible relations in requirements engineering decision–making. The questions identifying the respondents’ context and background are based on the facets identified by Paech et al. (2005).

The questions concerning the possible relationships within requirements engineering decision–making were structured using a three-point Likert scale for effectively measuring the experiences of the respondents (Jacoby and Matell 1971). We asked the respondents to state whether a certain characteristic influenced the decision lead–time in a positive, neutral or negative way. All relations examined based on the decision log were also inquired in the questionnaire. For example, a question from the survey was: “Please indicate how the number of products affected by the decision
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influences the time needed to take the decision”. The answer categories were: “This makes the time
to decide shorter”, “No influence” or “This makes the time to decide longer”. During the analysis,
we rated the first answer as a score of $-1$, the second answer as 0 and the last answer as $+1$. This
schema allowed to determine how strongly a certain decision characteristic influenced the decision
lead–time or outcome. The survey questions can be accessed at (Wnuk 2012) and in the Appendix A.

4.3. Validity

We discuss the validity of our research design and the results based on the classification proposed
by Yin (2008).

4.3.1. Construct Validity It is important to use the right sources for measuring the theoretical
constructs (Yin 2008). If we, for example, want to measure the time needed to take a decision, a
reliable source is needed to determine this amount of time. We analysed the decision log that was
actively used in the decision–making process at the case company. This decision log is an archival
record, which could be considered as stable, exact and quantitative. Whenever decisions in the
log were incomplete or ambiguous, we discussed them with the responsible product manager to
avoid making wrong interpretations. These discussions can be seen as interviews we had with the
responsible product manager. Both data collection methods (survey and analysis of work artifacts)
are highly applicable to software engineering case studies (Runeson and Höst 2009). Wohlin et al.
mentioned additional design threats to validity (Wohlin et al. 2000), namely the mono-operation and
mono-method bias threats. These threats concern creating a bias while using respectively one case
or method within the research. We ensured the validity on these levels by discussing all results with
a responsible product manager and the use of several statistical and qualitative methods to analyse
the data.

Construct validity of the survey part of the study is mainly concerned with the way that
questionnaire questions were phrased. To alleviate this threat to construct validity, an independent
senior researcher experienced in the topic reviewed the questionnaire. Moreover, we conducted
a pilot study to measure the time required to conduct the survey and minimize the risk of
misunderstanding or misinterpreting the survey questions by respondents. Further, the anonymity
of questionnaire respondents was guaranteed which minimized the evaluation apprehension threat.
Finally, we partly addressed the mono-operational bias by collecting 50 responses.
4.3.2. Internal Validity  Threats to internal validity concern the investigated causal relationship between studies factors (Yin 2008). In this study, we have minimized threats to internal validity by investigating as many possible factors that could influence the decision lead–time and outcome as it was possible with the given dataset. The identified relationships were validated against the results from the survey in which these relationships were further tested. Finally, the potentially impacting additional confounding factors for the studied relationships were discussed in all cases in which the results from the case study and the survey were inconsistent (see Section 5).

To avoid stating false inferences (Yin 2008), we have based our results on empirically derived data from a large company and validated the results in a survey. Finally, we discuss the achieved results in Section 5, by providing several possible explanations and possibilities, especially when the results from the case study and the survey are inconsistent.

4.3.3. External Validity  The external validity is considered as a main threat to validity in case studies due to difficulties to generalize from a single company study (Yin 2008) even if the size of the data sample is large. In an attempt to mitigate this threat, we designed and conducted a survey in order to validate the findings from the case study. Since the majority of survey respondents worked in smaller companies with a typical project generating not more than 100 requests, we could further strengthen the generalizability of the results by comparing a large context with smaller contexts. Despite this effort, with only 50 respondents of the survey the study remain exploratory and more research effort is needed to validate if the results are generalizable to other contexts, domains and companies. Finally, it should be mentioned that the data analysis in the first part of the study was one-dimensional (based only on the decision log) and conducting follow up interviews would have been valuable for strengthening external validity.

4.3.4. Reliability  In order to ensure the reliability of our study, we recorded the most important activities of the study in a case study protocol (Yin 2008). In this way, the performed research could be retraced. We also stored all artifacts from the case study, so conclusions based on the evidence can be retraced as well. The process of extracting the information from the decision log was supervised by one practitioner from industry. Further, we have published the survey questionnaire questions on-line (Wnuk 2012), described the sample population in Sections 4.2.2 and 5.2.1 and stored survey answers. However, we would like to stress that the data given by respondents is not based on any objective measurements and thus its subjectivity may affect the interpretability of the results.
5. RESULTS AND DISCUSSION

5.1. Test Selection

Selecting the appropriate test for analyzing the relationships is critical for getting reliable and scientifically sound results to base the conclusions on (Ott and Longnecker 2008). The choice of the right statistical test is dependent on three major factors, namely (Sheskin 2004):

- The level of measurement of the variables
- The distribution of the data
- The hypotheses that will be tested

We analyzed five different decision characteristics, which were all translated to quantitative, analyzable variables.

In order to perform parametric tests, all ratio level data should be distributed normally (Field 2009). Since the variable lead–time is the only variable of ratio level of measurement, we ensured this variable complied to the condition stated before. The variable lead–time apparently described a log–normal distribution, so in order to be able to use this variable, the \( \log_{10} \)-function of the variable was used for analysis. The detail of the transformation are depicted in Figure 3. The D’Agostino-Pearson test (1973) was used to see whether the \( \log_{10} \)-function of the variable lead–time described a Gaussian curve, or was distributed differently. We tested the following hypotheses (\( H^0 \)):

\[ H^0: \text{The sample is derived from a normally distributed population.} \]
$H_0^0$: The sample is not derived from a normally distributed population.

When testing the kurtosis and skewness (DeCarlo 1997) of the distribution, we found a result of $\chi^2(1, N = 753) = 35.3, p < .01$, which is below the critical value of 67.4 as can be found in the $\chi^2$ distribution table. This means we can not reject $H_0$, so we can conclude that the $\log_{10}$-function of the variable lead–time is distributed normally and we can use parametric tests on this variable. However, since the other analyzed variables are either of ordinal or nominal level of measurement, we also used non-parametric tests while analysing their influences and relationships.

5.2. Survey Data Analysis

The answers from the survey create variables of ordinal level of measurement. According to Stevens et al. (1946) median and percentile scores should be used as ways of assessing these types of survey results. In our case, calculated medians are means and at least half of the sample has identified a negative relationship. When the median is positive, at least half of the sample in our study has identified a positive relationship, see Table V and a frequency table can be used to further analyze the results.

5.2.1. Demographics

The survey was answered by 50 respondents. 32% of the respondents came from The Netherlands, 14% from Sweden and 46% came from other countries, including US and UK. Software project (12%) and product manager (48%) roles dominated among our respondents, followed by senior management (12%), consultants (12%) and developers (6%). Our respondents reported, on average, 13 years of professional experience, with standard deviation of about 6 years. Three respondents indicated having less than 5 years of experience: (1) one project manager from the US who worked with off–the–shelf solutions in a small company reported having one year of experience, (2) one requirements engineer from The Netherlands working with bespoke software with an average of 100 change requests per project reported having 2 years of experience and (3) one product manager from The Netherlands working with off–the–shelf product with an average of 10 requests per project reported having 4 years of experience.

The majority of the respondents (68%) worked with companies, in which up to 100 persons were involved in the software engineering process. Further, 52% of the respondents created mostly off–the–shelf software, followed by bespoke software (28%). When looking at the number of change requests per project, a typical project generates not more than around 100 requests for over 70% of the respondents. Finally, 64% of the respondents reported using the SPL approach (Pohl et al 2005).
Table IV. Survey results - the influence of decision characteristics on the decision lead-time, research question RQ1 and survey question 8, see Appendix A.

<table>
<thead>
<tr>
<th></th>
<th>This makes the time to decide shorter</th>
<th>No influence</th>
<th>This makes the time to decide longer</th>
<th>Rating average/Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>The request affects a high number of products</td>
<td>9.3%</td>
<td>9.3%</td>
<td>81.4%</td>
<td>0.72 / 1</td>
</tr>
<tr>
<td>The request is late in the release cycle (high release number)</td>
<td>53.5%</td>
<td>30.2%</td>
<td>16.3%</td>
<td>-0.37 / -1</td>
</tr>
<tr>
<td>The request is filed by an important customer</td>
<td>62.8%</td>
<td>23.3%</td>
<td>14.0%</td>
<td>-0.49 / -1</td>
</tr>
</tbody>
</table>

5.3. Factors that affect the decision lead–time: RQ1

Table V shows a list of all hypotheses together with their survey result medians (last column). Column “Level of Significance” supplies all test results, together with their critical values for the analysis of the decision log. The last column in Table V represents the median score for the survey answers.

To investigate which decision characteristics have a significant impact on the decision lead–time, we have tested three hypotheses (see the subsections that follow) and validated the results from the hypotheses testing with the results from the survey, see questions 1 to 3 in Table IV.

Table V. The results of the hypotheses testing on the data from the decision log together with the median score from the answers from the survey (last column)

<table>
<thead>
<tr>
<th>$H^e$</th>
<th>Case Study Results</th>
<th>Level of Significance</th>
<th>p-values</th>
<th>Median from the survey</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H^1$</td>
<td>Significant</td>
<td>$\rho = .222 &gt; .197$</td>
<td>p&lt;0.05</td>
<td>1</td>
</tr>
<tr>
<td>$H^2$</td>
<td>Not significant</td>
<td>$\rho = .180 &lt; .197$</td>
<td>p&lt;0.05</td>
<td>-1</td>
</tr>
<tr>
<td>$H^3$</td>
<td>Not significant</td>
<td>$p = .558 &gt; .05$</td>
<td>p&lt;0.05</td>
<td>-1</td>
</tr>
<tr>
<td>$H^4$</td>
<td>Significant</td>
<td>$Z = .545 &gt; .440$</td>
<td>p&lt;0.01</td>
<td>-1</td>
</tr>
<tr>
<td>$H^5$</td>
<td>Significant</td>
<td>$Z = 2.566 &gt; .440$</td>
<td>p&lt;0.05</td>
<td>-1</td>
</tr>
<tr>
<td>$H^6$</td>
<td>Significant</td>
<td>$\chi^2 = 7.032 &gt; 2.710$</td>
<td>p&lt;0.01</td>
<td>1</td>
</tr>
<tr>
<td>$H^7$</td>
<td>Significant</td>
<td>$t(752) = 3.940, p = 0.01$</td>
<td>p&lt;0.01</td>
<td>0</td>
</tr>
</tbody>
</table>

5.3.1. The impact of the number of products that a decision affects on the decision lead–time: $H^1$

Based on Hogarth et al. who stated that the time needed to take a decision is highly dependent on the task complexity (Hogarth 1975), we suspect a relationship between the number of products affected by a decision, e.g. the decision complexity, and the decision lead–time. The hypothesis testing this relationship ($H^1$, see Table V) can be stated as:
$H_0^1$: The correlation between the number of products affected by a decision and the lead–time needed to take the decision is 0.

$H_1^1$: The correlation between the number of products affected by a decision and the lead–time needed to take the decision is not 0.

Because we tested the correlation between a variable of ration level and of ordinal level of measurements, we used the non–parametric Spearman’s Rank-Order Correlation Coefficient (Spearman 1904). We found $\rho(752) = .222, p < .05$ after performing the test, which is higher than the listed critical value of .197 at a two–tailed level of significance of .05. This means we can reject hypothesis $H_0^1$ and accept the hypothesis $H_1^1$ that the correlation between the number of affected products and the lead–time is not 0. Stated more general: when the number of products affected by a decision increases, the lead–time needed to take the decision also increases. Since the correlation coefficient is rather low, the number of products may not be the only variable influencing the lead–time.
Looking at Figure 4 there appears to be no clear function to predict the time needed to take a decision when the number of products is known, but there are some indications of a positive trend to be seen. For example, if we compare the average lead–time for 1 product with the lead–time for 7 products, the lead time becomes about four times longer. However, if we look at the lead–time for 1 product (least number) and 14 products (highest number), we can see an decrease of almost 50% in average lead–time. This suggests that even with statistically significant correlation, other factors may also impact the decision lead–time.

The results of the survey show a positive relationship between the decision lead–time and the number of products affected by the decision, see second row in Table IV. 81.4% of the respondents confirmed that a high number of products affected by the decision make the decision lead–time longer. This result supports the value of the median in the first row of Table V.

The concordance between the results from the decision log analysis and the survey could be interpreted as an indication that more complex investigations take more time, which confirms that the results achieved in the experiments reported by Hogarth (1975) could be extended on requirements engineering decision–making. Further, our results in relation to this factor complement our previous findings (Wnuk et al 2011) that for large projects change proposals investigations take more time than for smaller projects. Finally, the possible practical conclusion from these results could be that if decisions have to be made quickly, their complexity should be reduced, e.g. by splitting one bigger errand into two or using other heuristics to reduce their complexity (Garcia-Retamero and Hoffrage 2006).

5.3.2. Effect of a certain release number on the decision lead–time: \( H^2 \)  
To study the relationship between the release number of the product line platform attribute of the change requests and the decision lead–time, we have tested the following hypothesis (\( H^2 \), see Table V):

\[ H_0^2 : \text{The correlation between the release number of the product line platform attribute of the change requests and the lead–time needed to take the decision is 0.} \]

\[ H_{1}^{2} : \text{The correlation between the release number of the product line platform attribute of the change requests and the lead–time needed to take the decision is not 0.} \]

We used Spearman’s Rank-Order Correlation Coefficient to test the correlation between a variable of ordinal level (release number of the product line platform) and a variable of ratio level (lead–time). The result of this test is \( \rho(752) = .180, p < .05 \), what is below the critical value of \( \rho = .197 \) for an \( \alpha = .05 \) two–tailed level of significance (see Table V). This means we can’t reject \( H_0 \) and...
we can’t state that there is a statistically significant correlation between the product line platform release number that changes impact and the lead–time needed to take a decision on our dataset.

The results of the survey regarding this aspect, see the third row in Table IV, show that 53.5% of the respondents suggested that decisions made late in the release cycle have a shorter lead–time. On the other hand, 30.2% of the respondents indicated that this factor has no influence on the decision lead–time and 16.3% of the respondents indicated that this factor makes the time to decide longer. To summarize, the results from the survey seems to contradict with the results from the decision log statistical analysis.

One possible interpretation of the discrepancy between the results from the survey and statistical analysis of the decision log may be related to the case company context factor. The lack of statistically significant relationship should be interpreted in the light of the result regarding hypothesis \( H^1 \). Since more complex decisions have longer decision lead-times, see hypothesis \( H^1 \), this would suggest that decisions affecting late product line platform releases at the case company have limited complexity. The process used by the case company seems to confirm this assumption as the early (major) releases are providing the main functionality of the product line platform and thus more complex decisions should be made for these early releases, see Section 3.

At the same time, the above assumption about the dominance of less complex decisions that affect late product line platform releases could also be interpreted as valid for the survey results. The demographics of the survey respondents, see Table 5.2.1, suggest that the decisions investigated by our survey respondents are less complex than decisions investigated in the case company. This, in turn, may suggest that the lead-time for later software product line releases decreases. Another possible factor affecting the survey results may be the type software projects that the majority of the survey respondents are involved in. In bespoke software projects the scope of the project is often set or implied as a contract and only minor adaptations or changes are allowed (Regnell and Brinkkemper 2005). Thus, the decision lead-time may decrease even for later software product line releases.

5.3.3. Effect of Important Customers on the decision lead–time: \( H^3 \) To test the effect of the type of customer that issued a request on the decision lead–time, we categorized the decisions into two categories. The first category are decisions that are requested from somewhere within the company (1003 decisions, 69.7%, were categorized into this category), while the second category are decisions that are requested by important external customers of the case company (436 decisions, see also Section 4.2.1). The following hypothesis was formulated in this case (\( H^3 \), see Table V):
$H_0^3$: The average lead–time needed to take a decision is not different when an important customer issues a request.

$H_1^3$: The average lead–time to take a decision is different when an important customer issues a request.

The t–test (Cramér 1945, Student 1908) results ($t(752) = .586, p = .558$, see $H^3$ in Table V) does not allow us to reject $H_0^3$. Therefore, we can state that based on our data there is no significant difference between the lead–time needed to take decision when the decision is requested by an important customer. One possible explanation could be the fact that all decisions follow the same decision process at the case company so it doesn’t matter which customer issued a change request. Another possible explanation may be that 31.3% of the analyzed requests were issued by important external customers which may have influenced the results. Finally, another possible interpretation of this result may be that the case company does not pay enough attention to the requests of important customers and thus their lead–times are longer. If that is the case, introducing prioritization of change requests may be a possible workaround.

The result of the survey (see Table IV) shows a negative relationship (requests issued by important customers have shorter lead-times), in contrast to the statistical analysis indicating no relationship, see $H^3$ in Table V. Moreover, 62.8% of the respondents reported that time to make the decision is shorter when the decision is filed in by an important customer while 23.3% of the respondents reported that this factor has no influence on decision lead–time.

The discrepancy between the results from the decision log analysis and the survey needs further investigation. In related work, Taylor et al. (2011) reported that the prioritization process is often favoring requirements from large customers and that this “greedy heuristic” produce good results when the customer base is small. At the same time, their preliminary results suggest no biases towards larger customers (Taylor et al 2011), which confirms our results (also conducted in a large–scale setting). However, the study by Taylor focused on the decision outcome rather than the decision lead–time. The possible summary conclusion from the results could be that, for smaller projects, the decision lead–time could be impacted by the type (size) of the customers issuing the requirements, while for larger contexts this relationship doesn’t hold.
5.4. Factors that affect the decision outcome: RQ2

In order to investigate which decision characteristics have a significant impact on the decision outcome, we have tested three hypotheses, $H^4$, $H^5$ and $H^6$, see the subsections that follow, and validated the results from the hypotheses testing with the results from the survey, see Table VI.

Table VI. Survey results - the influence of decision characteristics on the decision outcome, research question RQ2 and survey question 9, see Appendix A

<table>
<thead>
<tr>
<th></th>
<th>This increases the probability of rejection</th>
<th>No influence</th>
<th>This decreases the probability of rejection</th>
<th>Rating average / Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>The request affects a high number of products</td>
<td>$54.8%$</td>
<td>$33.3%$</td>
<td>$11.9%$</td>
<td>$-0.43 / -1$</td>
</tr>
<tr>
<td>The request is late in the release cycle (high release number)</td>
<td>$71.4%$</td>
<td>$26.2%$</td>
<td>$2.4%$</td>
<td>$-0.69 / -1$</td>
</tr>
<tr>
<td>The request is filed by an important customer</td>
<td>$9.5 %$</td>
<td>$7.1%$</td>
<td>$83.3%$ (35%)</td>
<td>$0.74 / -1$</td>
</tr>
<tr>
<td>The decision took a long time to make</td>
<td>$26.2%$</td>
<td>$57.1%$</td>
<td>$16.7%$</td>
<td>$-0.10 / -1$</td>
</tr>
</tbody>
</table>

5.4.1. The impact of the number of products that a decision affects on the decision outcome: $H^4$

To test the relationship between the decision outcome and the number of products affected by the decision (referred as $H^4$ in Table V), we have formed the following hypothesis:

$H_0^4$: The number of products affected by a decision is not different for the different decision outcomes.

$H_1^4$: The number of products affected by a decision is different for the different decision outcomes.

We used the Kolmogorov-Smirnov test for two independent samples to test the relationship between an ordinal level variable and a nominal level variable (Smirnov 1939). We found a result of $Z = .545, p < 0.01$, which is higher than the reported critical value listed for Kolmogorov-Smirnov’s Z at this level of significance. This means we can reject $H_0^4$ and accept our alternative hypothesis. Thus, we can conclude that there is a high likelihood the two groups are derived from different populations. More precisely, we can say that the data indicates that rejected decisions have a lower number of products they affect.

A significant relationship was also discovered between the number of products affected by a decision and the decision lead–time, see Section 5.3.1. Thus we can state with a high certainty that
there is a relationship between the decision complexity, the decision outcome and time needed to
take a decision in the case company, as suggested in the literature (Hogarth 1975). Our results
complement related research (Bagnall et al 2001, Saliu and Ruhe 2005) that also suggested a
possible relationship between release planning and decision quality.

The survey results, see the first row in Table VI, disprove the statistical analysis of the decision
log since 54.8% of the respondents answered that a high number of products affected by the decision
increases the probability of rejection. This contradicting result could be caused by the fact that in the
case study dataset more rejected than accepted decisions affected only one product. In other words,
the case company seems to be more eager to reject than accept small change requests. This may have
economical basis if we assume that change requests affecting only one product weakly contribute
to increase revenue generation. In this case, it appears to be more logical to reject those change
requests and focus on more complex change requests are potentially more promising additional
revenue contributors.

Another possible explanation for the conflicting results between the decision log analysis and the
survey could be the fact that the majority of the survey respondents (68%) worked with companies
up to 100 persons involved in a project and a typical project with not more than around 100 requests.
This may suggest that the complexity, understood as the number of products involved in the decision,
does not influence the rejection of issued requests for larger projects, but it could for smaller projects.
Also, with a low number of around 100 requests per a typical (bespoke) project, project management
may need to focus on investigating and possibly accepting all change requests from the customers.

Since most of the survey respondents worked with software product line approach (64%) hence
some respondents admitted to work with bespoke and off–the–shelf software, this may suggest that
in those contexts complex investigations are more likely to be rejected than accepted. However, this
assumption needs to be further investigated for significance. In related work, Wnuk et al. (2009a)
reported five main reasons for excluding feature candidates from the scope of the project. Our results
suggest that the complexity is an additional factor that should be further investigated.

5.4.2. Effects of a certain release number on the decision outcome: $H^5$
As the second relationship investigated for RQ2, we tested if the product line platform release number attribute impacts the
decision outcome. We stated the following hypothesis (referred as $H^5$ in Table V) and validated the
results with the results from the survey, see the third row in Table VI:

$H^5$: The release number a decision affects is not different for the different decision outcomes.
The release number a decision affects is different for the different decision outcomes.

We used the Kolmogorov-Smirnov test for two independent samples, which resulted in a score of $Z = 2.566, p < 0.01$ (see Table V). This result is above the documented critical value of Kolmogorov-Smirnov’s $Z$, what means we can reject $H_{50}$ and accept the alternative hypothesis $H_{51}$. Thus, we can state that the chances of accepting a request are higher if that request affects a release late in the release cycle.

The results from the survey show an opposite relation, see the third row in Table VI. 71.4% of the respondents indicated that requests affecting products with higher release numbers (planned to be released late in the release cycle) are more likely to be rejected. We suspect this contrast in results between the survey and the case study could be caused by the fact that the case company is simply getting more requests for late releases (65.5% of all requests). Another possible explanation may be that customers could use the products released in the beginning of the release cycle as a potential source of requests for future releases. This could explain the contrasting results between the decision log analysis and the survey. Moreover, since late platform releases are focusing on smaller adaptations of the platform, this may also impact the results.

The fact that the respondents mainly worked with smaller projects than investigated at the case company could also be the cause of the discrepancy of the statistical analysis and survey results. To summarize, the results from the case study and from the survey suggest that the release that decisions concern could be an additional factor that influences decision outcomes and this result complements published related work (Barney et al 2008, Ruhe and Saliu 2005, Wnuk et al 2009a, Wohlin and Aurum 2005). However, the discrepancy between the case study and the survey results suggest that the direction of the relationship may not always be the same.

5.4.3. Effect of Important Customers on the decision outcome: $H_6^6$ For the last factor that could affect decision outcome, we have tested if there was any effect on the decision outcome caused by the type of the customer that issues a change request. In order to test this relationship, we performed a $\chi^2$ test for $r \times c$ tables. This test is suitable for analyzing correlations between two nominal variables.

Our hypothesis ($H_6^6$ in Table V) is:

$H_6^5$: The frequencies in the contingency table between the decision outcome and involvement of important customers do not differ from the normal expected frequencies.
$H_6^0$: The frequencies in the contingency table between the decision outcome and involvement of important customers differ from the normal expected frequencies.

The result of this test is with $\chi^2(1, N = 1439) = 7.032, p < .01$ above the listed critical value. This means we can reject $H_6^0$ and accept our alternative hypothesis. Since the value of $\chi^2$ is rather low, we can state that the change receives a positive decision outcome when it is requested by an important customer. Looking deeper, we identified that 11% more decisions originate from customers than internal departments.

The majority of the survey respondents (83.3%, see row 3 in Table VI) indicated that the importance of the customer that issues the request decreases the probability of rejection, in other words increases the probability of acceptance. Since the value of $\chi^2$ test above is rather low this may indicate that the fact that requests from important external customers were more likely accepted at the case company could be a company specific phenomenon, or related the project size as the survey respondents most likely worked with projects with fewer than 100 requests.

In the related study, Taylor et al. (2011) suggested that larger customers more likely get their requirements accepted, but the paper lacks statistical analysis of the mentioned correlation. Moreover, our results from the statistical analysis regarding the influence of the importance of the customer on the decision lead–time $H^3$ and the decision outcome $H^6$ are not consistent, which could suggest additional uncovered factors. Another possible explanation is that since all requests follow the same process, their lead–time does not depend on the importance of the issuer.

Ruhe and Saliu (2005) suggested that the release decisions are made by “contracting the main stakeholders and manually balancing their interests and preferences” which we interpret as accepting more features from important (main) stakeholders. Finally, our results confirm the viewpoint of Bagnall et al. (2001), who suggested that requirements from “favored customers” will be viewed as more important than other requirement and thus those requirements will be more often accepted.

5.5. Effect of lead–time on the decision outcome - RQ3

The last relationship we examined is whether the lead–time influences the decision outcome. To test this relation, we stated the following hypothesis (stated as $H^7$ in Table V):

$H^7_0$: The average lead–time needed to make a decision does not differ per decision outcome.

$H^7_1$: The average lead–time to make a decision does differ per decision outcome.
After categorizing decisions to accepted and rejected decisions, we calculated their average lead–times. The average lead–time for accepted and rejected decisions is respectively $\mu = 1.12$ and $\mu = .98$. The t–test result ($t(752) = 3.940, p < 0.01$, see the last row in Table V) indicated a significant differences between the average lead–time for both decision outcomes. This means we can accept $H_1^7$ and reject the null–hypothesis $H_0^7$. Based on these results, we can state that the average lead–time needed to reject a decision is statistically significantly longer than the lead–time needed to accept a decision.

When looking at the survey results presented in the last row in Table VI, we see that 57.1% of the respondents indicated that the time to make the decision does not influence the decision outcome. The statistical analysis of the survey results for this question showed a neutral relationship (median equals to 0, see last row in Table V) which prevents us from drawing strong conclusions. However, it is worth noticing that 26.2% of the respondents agreed with the statistically significant result of the decision log analysis.

There could be several possible causes of the discrepancy between the decision log analysis results and the survey result in regards to this aspect. One possible explanation could be the size of the projects analyzed in the case study and by the survey respondents. Since the questionnaire respondents mainly worked with projects that generate not more than 100 requests and with smaller companies, we suspect that the complexity of the issued changes in those contexts is smaller than in the case of the case company investigated. As a results, those assumingly less complex decisions could be proceeded more quickly by our questionnaire respondents than by the practitioners from the case company, as suggested by Hogarth (1975). Thus, the survey respondents might have not been able to experience as long decision lead–times as the case company practitioners and thus for them this factors does not influence the decision outcome.

Moreover, since the case company operates in the MDRE context, the time pressure to investigate and decide upon incoming requirements is high. Excessive deposition of decisions may cause serious consequences for the success of software projects in the MDRE context as time–to–market is critical (Regnell and Brinkkemper 2005). For long investigations, decision makers could simply be forced to reject the proposal due to a missed market–window opportunity and this could be one of the possible explanation of the statistically significant result. This interpretation could be supported by the fact that more than 1/4 of the survey respondents worked with bespoke software projects. Furthermore, as visualized by Wnuk et al. (2009a), accepting new features to the project scope is much easier than reducing the scope which is often performed during the entire time of the project.
6. DISCUSSION

The current study found that more complex change requests (affecting more products) have a longer lead-time. The possible practical implication of this result is that the complexity of change requests should be monitored and, if needed, reduced in order to keep the decision-making process efficient. Another important finding from the statistical analysis is that change requests affecting a lower number of products are more often rejected. A possible explanation for this might be that in SPL development smaller and less complex changes will mostly not be integrated into the software platform, causing significant testing, compatibility and change management efforts. Therefore, practitioners could be more eager to accept more complex errands that could more easily be integrated into the platform and serve all customers.

Contrary to expectations, the results regarding the effect of a certain release number on the decision lead-time and outcome are in contrast. The survey results bring weak evidence that decisions affecting late releases have shorter lead-times. At the same time, these change requests have a higher change of acceptance, according to our statistical analysis. However, this result was disproved by the survey respondents. It can thus be suggested that practitioners should be more careful when accepting late changes as they could potentially destabilize the development effort and cause serious delays (Brooks 1995).

Supported by our results regarding the effect of important customers on the decision outcome and lead-time, we advise practitioners to follow the requests of important customers and resolve them as quickly as they can. However, we would also like to alert practitioners to keep their eyes on requests coming from less important customers. Due to the multiplicity of smaller customers, their requests could also provide valuable source of revenue (Taylor et al 2011) and therefore should not be desk rejected neither lengthy analyzed.

Practitioners working in large projects should be aware that the lead-time for rejected decisions could be significantly longer than for accepted decisions. This is particularly important when facing several late change requests close to the product or project release date. Analyzing and resolving these requests may require thorough analysis, the task that is in most cases (70%) skipped (Samalikova et al 2009). This creates a risk when directly resolved change requests are not based on thorough analysis and reasonable arguments. We recommend checking the market window of the proposed changes and, if possible, dedicating more time for the change impact analysis.
7. LIMITATIONS

The relationships were not analyzed in relation to the phase of the project (milestones M1 to M7, see Section 3) they arrived. It seems possible that our results could have been influenced by this factor. Therefore, we consider this as a limitation and plan to tackle this issue in future work. Furthermore, the contrasting results between the statistical analysis and the survey results suggest possible additional confounding factors influencing the decision lead-time and outcome. The exploratory nature of this study gives good starting point for further exploration of the factors affecting decision making in requirements engineering.

The relatively low number of survey answers (50) is another clear limitation of our study. Furthermore, the single case described in this work is hard to generalize to the entire software industry. Therefore, the transferability of our results need to be interpreted with caution. Finally, another limitation is the fact that we categorized the change requests into arriving from external customers and internal. This creates a risk of wrong classification. however, this risk is low as the classification was based on available information and consulted with practitioners from the case company.

We make the tacit assumption that requirements decision–making is a sequence of isolated or exclusive decisions. This assumption poses a threat to the validity of our results and we provide no evaluation of the extent to which this assumption is realistic. Other authors suggested that decision are inter-related, with each decision leading to further decisions (McAvoy and Butler 2009). Therefore, it would be interesting to explore if analyzed decisions could be connected into chains which often spans the entire project duration.

The insight on whether a specific decision is right is very hard to determine. For example, looking from the product success perspective, the success or failure of a software product is extensively hard to track down to a single feature acceptance or rejected. The customer value (and market success) builds from a set of features and is also heavily determined by the market situation and other often uncontrollable factors. Furthermore, some features pay off on short term while other features on long term and only in combination with other "enabler" features. Product differentiation appears to be caused by differences in distribution and awareness than differentiation on functional feature level (Sharp and Dawes 2001). Moreover, it is valuable to investigate the role of decision–making in the software value creation process (Khurum et al 2012). Therefore, we believe that it is the topic for future work to investigate whether or not the decisions made were the right decisions. Finally, hesitations to take decisions could be considered as a part of the lead-time drive. Some decision
makers could be more eager to decide quickly with more uncertainties while others would rather more time on issue evaluation before decisions are made. It is a part of future work to investigate this aspect.

8. CONCLUSIONS


In this paper, we report on an investigation of decision–making in requirements engineering. We analyzed 1439 change requests looking for statistically significant relationships between the decision–making factors i.e., number of products, release number, type of customer and decision lead–times and outcomes. The results from this analysis were validated with the results from a survey among 50 practitioners from several countries involved in decision–making processes. The results from the study could be summarized in the following points:

- The lead–time to make a decision increases when more products (considered as a proxy for the decision complexity) are affected by this decision - this result was confirmed both in the statistical analysis and in the survey. Since the relationship is rather clear, decision makers should be aware that too complex decisions may take a long time (research question RQ1).
- There is no significant relationship between the release of the product line that a change request impacts and the decision lead–time according to the results from the statistical analysis of the decision log. At the same time, the majority of the respondents in the survey suggested that decisions made late in the release cycle have shorter lead–times (RQ1).
- The lead–time for decisions is shorter when the change requests are issued by important customers, according to the respondents. The statistical analysis of the decision log disproved this suggestion. Therefore, no clear relationship was identified for this factor (RQ1).
- The statistical analysis showed that if a request affects a lot of products, it has a higher change of being accepted (RQ2). The respondents of the survey stated that requests that affect a lot of products have a higher change of being rejected. This may seem counter-intuitive, but this is
probable caused by the fact that request that affect a lot of products are often requests related to the platform and thus are important.

- Change requests affecting late releases have a significantly higher probability of acceptance according to the statistical analysis of the decision log (RQ2). This result seems to be more characteristic for large contexts as the results from the survey, in which most respondents worked with projects with fewer than 100 decisions, indicate the opposite relationship with a higher probability of rejecting these requests.

- Change requests issued by important customers are more likely to be accepted, (RQ2) according to the statistical analysis of the decision log. This relationship was confirmed by a clear majority of survey respondents (83.3%).

- The lead–time to reject a decision is significantly longer than to accept a decision (RQ3), according to the statistical analysis of the decision log. At the same time, the results from the survey suggests that there is no relationship between the lead–time and the decision outcome.

Our results clearly indicate that the number of products affected by a decision increases the decision lead–time (research question RQ1). This result has a practical importance for requirements engineering decision makers. As more complex decisions take more time, it may be wise to decrease their complexity for more quickly decisions. This could be particularly useful in MDRE, in which time to market pressure is inevitable (Regnell and Brinkkemper 2005). Our study reports that lead–times could become up to 400% longer if a complex decision affects multiple products.

Our results also confirm that the importance of the customer who issues a change request increases the probability of acceptance (research question RQ2). These requests have an 11% higher change to be accepted than other requests. Product management processes could be adapted when being aware of the supported relationships. For example, the change process of Figure 1 can be refined by asking for additional details from more important customers in order to reduce the lead–time.

Regarding the relationship between the decision lead–time and the decision outcome (research question RQ3), we report based on the analysis of the decision log that the average lead–time needed to reject a decision is statistically significantly longer than the lead–time needed to accept a decision. This result couldn’t been confirmed by the survey respondents. Decision makers could use this conclusion when planning for effective pruning of possible decisions for a project. At the same time, this relationship seems to hold for larger projects, as the results from the survey suggests that there is no relationship between the lead–time and the decision outcome.
Future research is planned to go more in depth on the possible relationships among requirements engineering decision-making characteristics. Two relationships could be proven and quantified by us, but the other five relationships need further research in order to further explore them. Within the two relationships proven by us, more research is needed as well. For instance, it would be helpful and desirable if a function could be formulated to estimate the lead-time or the chance on a certain decision outcome. Furthermore, the notion of complexity should be extended by modularity, coupling and cohesions of the architecture. The impact of architectural complexity on decision lead-time and outcome should be explored in future studies s it might influence the success of the product in terms of meeting requirements.

Other decision characteristics, such as the number of stakeholders involved of the number of dependencies between software components, could also be of relevance for the decision lead-time or outcome. Due to lack of data, these characteristics have not yet been taken into account in this research, but could be considered in the scope for future research. While importance of customer and number of products impacted were mentioned as variables, neither the total projected volume of product sold, nor the total revenue from product sold (e.g. the potential sales change after a change request is implemented) were considered. Thus, future work should focus on investigating the potential influence of the mentioned factors of decision lead-time and outcome. Finally, future work should also investigate thought processes that individuals go through when making a decision and whether these processes impact the decision lead-times or outcomes.

ACKNOWLEDGMENT

The authors would like to thank Thomas Olsson and Prof. Per Runeson for their suggestions in this research project. The authors would like to thank Dr. David Callele for excellent language comments. We also thank the survey respondents. This work was supported by the EASE project.

REFERENCES

Al-Emran A, Pfahl D, Ruhe G (2010) Decision support for product release planning based on robustness analysis. Sydney, NSW, Australia, pp 157 – 166, URL http://dx.doi.org/10.1109/RE.2010.28, decision supports;Multi-criteria decision analysis;Operational planning;Release planning;Robustness;Simulation;


Aurum A, Wohlin C (2005) Engineering and managing software requirements. Springer Verlag


D’Agostino R, Pearson E (1973) Tests for departure from normality. empirical results for the distributions of $b^2$ and $\sqrt{b^3}$. Biometrika 60(3):613


Smirnov N (1939) On the estimation of the discrepancy between empirical curves of distribution for two independent samples. Bulletin Mathematics University Moscow 2:3–14


A. APPENDIX: QUESTIONNAIRE QUESTIONS

A.1. INTRODUCTION

This is a short survey about decision-making in requirements engineering. When managing requirements, often the decision has to be made whether or not to accept a certain requirement request. These possible requirements all have different characteristics such as the number of products they affect or the fact that they are requested by an important customer.

The purpose of this survey is to assess which characteristics of submitted requirements change requests may influence the decision outcome and the decision lead-time. We already performed a quantitative analysis on the decision logs of a large software products company and we want to validate our results using experiences from other companies.

After your participation in the survey we will get back to you with the analyzed results of the survey and you will also get access to the results of the quantitative analysis of decision logs. Thanks in advance for your cooperation!

A.2. BACKGROUND

In order to compare your answers with our quantitative analysis results, we need to know some things about you, your company and your project context.

**Question 1: What region are you most active in?**

( ) The Netherlands
( ) Belgium
( ) Germany
( ) Sweden
( ) Worldwide
( ) Other (please specify)

**Question 2: What is your current role within the company?**

( ) Project Manager
( ) Product Manager
( ) Quality Expert
( ) Developer
( ) Senior Management
( ) Consultant
( ) Other (please specify)

**Question 3: How many years of professional experience do you have in software engineering?**

**Question 4: How many people are involved in the software engineering process in your company? Please consider all employees, including, but not limited to developers, testers and management.**

( ) < 10
( ) 10 - 100
( ) 100 - 500
( ) 500 - 1000
( ) > 1000

**Question 5: What kind of relationship does your company have with its customers?**

( ) We create mostly custom bespoke software
( ) We create mostly off-the-shelf software
( ) Other (please specify)

**Question 6: How many requirement requests does a project in your company have on average?**

( ) Around 10
( ) Around 100
( ) Around 1,000
( ) Around 10,000
( ) Other (please specify)

**Question 7: Does your company apply a software product line approach? (Does your company release a collection of similar software products from a shared set of software assets?)**

( ) Yes
( ) No
( ) Other (please specify)

### A.3. RATINGS

Please answer the questions below according to your own experiences. Please indicate how the following decision characteristics influence the time needed to take the decision.

**Question 8. Please indicate how the following decision characteristics influence the time needed to take the decision**

<table>
<thead>
<tr>
<th></th>
<th>This makes the time to decide shorter</th>
<th>No influence</th>
<th>This makes the time to decide longer</th>
</tr>
</thead>
<tbody>
<tr>
<td>There are a high number of products affected by the decision</td>
<td>( )</td>
<td>( )</td>
<td>( )</td>
</tr>
<tr>
<td>The decision is late in the release cycle</td>
<td>( )</td>
<td>( )</td>
<td>( )</td>
</tr>
<tr>
<td>The decision is filed by an important customer</td>
<td>( )</td>
<td>( )</td>
<td>( )</td>
</tr>
</tbody>
</table>

**Question 9. Please indicate how the following decision characteristics influence the decision outcome.**

<table>
<thead>
<tr>
<th></th>
<th>This increase the probability of rejection</th>
<th>No influence</th>
<th>This decrease the probability of rejection</th>
</tr>
</thead>
<tbody>
<tr>
<td>There are a high number of products affected by the decision</td>
<td>( )</td>
<td>( )</td>
<td>( )</td>
</tr>
<tr>
<td>The decision is late in the release cycle</td>
<td>( )</td>
<td>( )</td>
<td>( )</td>
</tr>
<tr>
<td>The decision is filed by an important customer</td>
<td>( )</td>
<td>( )</td>
<td>( )</td>
</tr>
<tr>
<td>The decision took a long time to make</td>
<td>( )</td>
<td>( )</td>
<td>( )</td>
</tr>
</tbody>
</table>