Software Quality Journal manuscript No.
(will be inserted by the editor)

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

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Received: date / Accepted: date

Abstract Lead-time is crucial for decision making in market-driven requirements engineering. In order to identify what factors influence the decision lead time and outcome, we conducted a retrospective case study at a large product software manufacturer and statistically analyzed seven possible relationships among decision characteristics. Next, we further investigated relationships among decision characteristics in a survey among industry participants.

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The results show that the number of products affected by a decision could increase the time needed to take a decision. Results also show that when a change request originates from an important customer, the request is faster accepted.

Keywords 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.

Large companies often use the software platform concept, also known as Software Product Lines (SPL) (Pohl et al 2005). SPL helps 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 a more complex decision making process.

The requirements selection process is a complex decision problem, bringing up several challenges, e.g. shifting goals, time stress (Alenljung and Persson 2008) 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 2008, 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.

In this paper, a retrospective analysis of the decision making process in a large–scale MDRE and SPL project is performed with the aim for 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. The decision lead–time is in this context defined as 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 results from analyzing the decision–log are further investigated in a survey among 50 industry respondents.

The main goals for the paper are threefold: (1) to explore possible factors that may influence decision lead–times, (2) to investigate the possible factors that may influence decision outcomes and (3) to investigate if the decision lead–time affects the decision outcome. Partial results from this study have previously been published as workshop publications in (Kabbedijk et al 2010). This paper extends our previous work by: (1) validating the results 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 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 6.

2 Related Work

Decision making is an important aspect of requirements engineering (Alenljung and Persson 2008, 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. Therefore, understanding of the nature of the decisions made in the RE process is necessary for improving it (Aurum and Wohlin 2003). Despite an increasing awareness for supporting RE decision making, research in this area is still "in its infancy" (Ngo-The and Ruhe 2005).

The requirements engineering process is a decision rich activity for which decisions can 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). As a result, the risk of making inappropriate decisions is high and the consequences of made decisions can be serious. Furthermore, RE decisions are often semi–structured or unstructured and made only once, which make the evaluations of the decision outcomes difficult (Ngo-The and Ruhe 2005). Moreover, Strigini (1996) stressed a lack of objective criteria for guiding making decisions, e.g. based on statistics about past experience which results in important decisions often depending on subjective judgments. Thus, empirical investigation of the factors that affect decision outcomes is important as it can contribute to more continuous, controllable and structured requirements engineering decision making.

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). Ruhe (2005) modeled release planning decisions by combining computational knowledge intelligence and experience of decision makers or by using linear programming (Ruhe 2009). van den Akker et al. used integral linear programming to find an optimal set of requirements within the given resource constraints that can maximize the revenue (van den Akker et al 2008). Chen et al. focused on time schedling aspect of release planning (Li et al 2010/11/). 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 to support requirements prioritization 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. However, 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.

Among the challenges in RE decision making Alenljung et al. (2008) 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. (2009); 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) or the complex dependencies between requirements (Cleland-Huang et al 2005). 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 2008, Aurum and Wohlin 2003, Berander and Andrews 2005).

Despite the above mentioned need for more empirical studies and several reported studies that outline challenges in requirements engineering decision making, 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. (2009) investigated the reasons for excluding features from the project's scope reporting that the stakeholder business decision is the dominant reasons for feature exclusions. 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. Moreover, Barney et al. (2008) 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.

While looking more generally at related work in decision making field, 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 hasn't been 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. However, the mentioned relationships haven't been empirically investigated in a large-scale MDRE context and especially in relation to decision lead–times and decision outcomes.

3 Case Company Description

The paper reports results from a content analysis (Lethbridge et al 2005) of the record of decisions made in an industrial project at the large company using the SPL approach (Pohl et al 2005). 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. The stage–gate model with several increments (Cooper 1990) is used by the company. The scope of the core release project is constantly changing during this process, from the initial roadmap 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.

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 exists of product and platform managers, complemented with other project stakeholders to a total of 20 members. 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.

Fig. 1 Change control board decision process

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. 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. In this way, the impact of a change on the cost and functionality of the system as well as on customers and other external stakeholders is assessed (Leffingwell and Widrig 2003). After the impact analysis, the request is presented at the CCB meeting and the change request is decided upon. 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.

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 that the rationale and effects of RE decisions on software product should be tracked in order to support and improve RE activities (Aurum and Wohlin 2003)

An example of an entry in the decision log is shown in Table 1. 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 (the release number is low) or in a later release (the release number i high). 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 all products planned to be released in 2008.

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 formulated research questions, see Section 4.1 about relations within requirements engineering decision making and hypotheses based on these questions, see Section 5. We run statistical tests on empirical data

Table 1 Decision log entry example

ID	54
Change Request	HD resolution for video
Decision Outcome	Accepted
Comments	This will enlarge our market share in this sector
Description of proposed change	Add HD resolution for recording
Justification	Requested by a large provider
Proposition Area	Video
Main affected Technical Group	Video Group
Affected product	All products with a camera
Affected key customer	Customer X
Affected Functional Group	HD Group
Submittal Date	09-02-09
RM tool ID	10F1
Decision Date	18-02-09

to either accept or reject hypotheses and draw conclusions based on the test results. The results of the statistical analysis were further validated in a survey and interpreted in relation to related studies.

4.1 Research questions

Three research questions are investigated in this paper and are outlined in Table 2, complemented with aim and example answers for each question. The questions were shaped and inspired by the related literature outlined in Section 2. All three research questions are relationship questions (Easterbrook et al 2008). The questions are further decomposed into hypotheses that were investigated using statistical tests, see Section 5.

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. After some point the costs of errors due to the task complexity becomes lower than the cost of time. This is the tilting point at which the amount of time becomes a decreasing function of the task complexity. In this paper, we empirically investigate 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

Table 2 Research questions

Research question	Aim	Example answers
RQ1: Which decision characteristics affect the decision lead–time?	To understand which decision characteristics i.e, number of products, release number, type of customer have a significant impact on the decision lead–time	The number of products involved in the decision increases the decision lead–time. Decisions that are related to the current release or consider our largest customers have shorter lead–times.
RQ2: Which decision characteristics affect the decision outcome?	To understand the relation between the decision characteristics and the acceptance or rejection of a decision	The number of products involved in the decision decreases the probability of accepting this decision. Decisions that are related to the current release or issued by important customers are usually accepted.
RQ3: Is the decision outcome related to the decision lead–time	To understand the relation between the acceptance rate and the decision lead–time	Decisions with longer lead–time are more often rejected

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 faster 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 2009). In our previous work (Wnuk et al 2009), 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. In a related paper, Zur (1981) claims a relationship between the time pressure people's 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 have 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

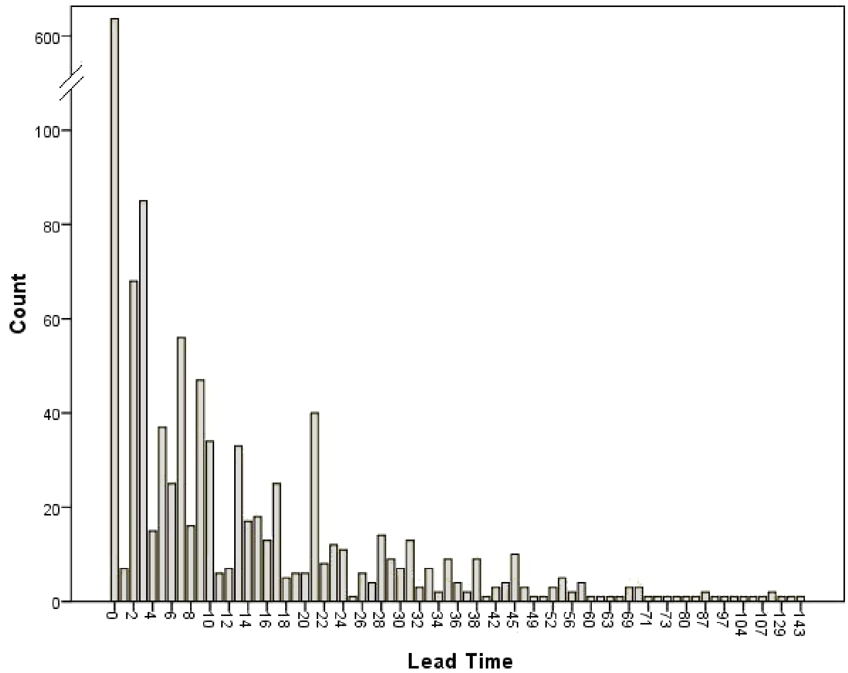


Fig. 2 Number of decisions taking a certain lead-time

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 will 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 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 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.

4.3 Validity

We discuss the validity of 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 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 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 how 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 minimize the evaluation apprehension threat. Finally, the mono-operational bias threat is to partly alleviated as we managed to collect 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 confronted with 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 confronted the results in a survey. Finally, we discuss the achieved results in Section 5, where we provide 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. To mitigate this threat, we have 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.

4.3.4 Reliability

In order to ensure the reliability of a study, it is important to have created a case study protocol and to maintained a case study database (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. Further, we have published the survey questionnaire questions on-line (Wnuk 2012) and described the sample population in Sections 4.2.2 and 5.2.1. 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.

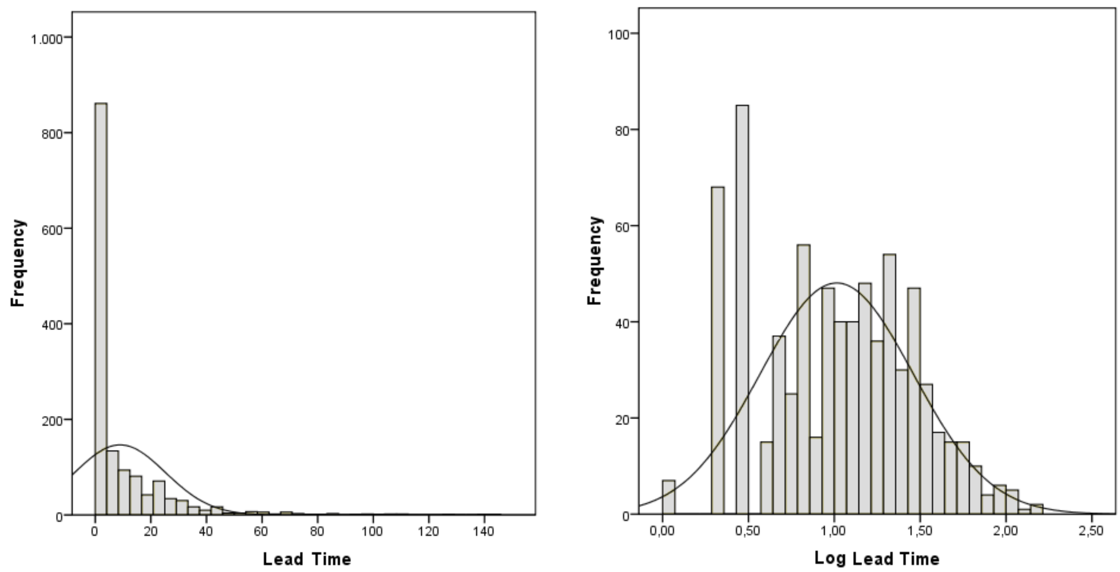
5 Results and Discussion

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.



(a) lead–time (b) Log_{10} lead–time

Fig. 3 lead–time Gaussian curve fit

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_0: The sample is derived from a normally distributed population.
H^0_1: 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 χ^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 meansand 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 4 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 3 Survey results - the influence of decision characteristics on the decision lead-time, research question RQ1 and survey question 8 (Wnuk 2012).

	This makes the time to decide shorter	No influence	This makes the time to decide longer	Rating average/Median
How a high number of product affects the decision lead–time, H^1	9.3%	9.3%	**81.4%**	0.72 / 1
The decision is late in the release cycle (high release number), H^2	**53.5%**	30.2%	16.3%	-0.37 / -1
The decision is filled by an important external customer, H^3	**62.8%**	23.3%	14.0%	-0.49 / -1

5.3 Factors that affect the decision lead–time: RQ1

Table 4 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 4 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 (H^1,H^2 and H^3, see the subsections that follow) and confronted the results from the hypotheses testing with the results from the survey, see Table 3.

5.3.1 The impact of the number of products that a decision effects 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 4) can be stated as:

Table 4 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)

H^x	Case Study Results	Level of Significance	Median from the survey
H^1	Significant	$\rho = .222 > .197$	1
H^2	**Not** significant	$\rho = .180 < .197$	-1
H^3	**Not** significant	$p = .558 > .05$	-1
H^4	Significant	$Z = .545 > .440$	-1
H^5	Significant	$Z = 2.566 > .440$	-1
H^6	Significant	$\chi^2 = 7.032 > 2.710$	1
H^7	Significant	$t(752) = 3.940, p = 0.01$	0

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.

We used the non–parametric Spearman's Rank-Order Correlation Coefficient (Spearman 1904) to assess the correlation size between a variable of ratio level and of ordinal level of measurement. 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 increases as well. Since the correlation coefficient is rather low, the number of products may not be the only variable influencing the lead–time.

Looking deeper, Figure 4 shows an increase of the average lead–time related to the number of products affecting change requests for the case company dataset. If we compare the average lead–time for 1 product with the lead–time for 7 products, the lead time becomes about five times longer. If we look at the lead–time for 1 product (least number) and 13 products (highest number), we can still see an increase of 130% in average lead–time. 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 is a clear positive trend to be seen. Therefore, the raise of the number of product is substantial.

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 3. 81.4% of the respondents confirmed that a high number of products affected by the decision make the decision lead–time longer. This result confirms the value of the median in the second row of Table 4.

The concordance between the results from the decision log analysis and the survey could be interpreted as an indication that more complex investigations

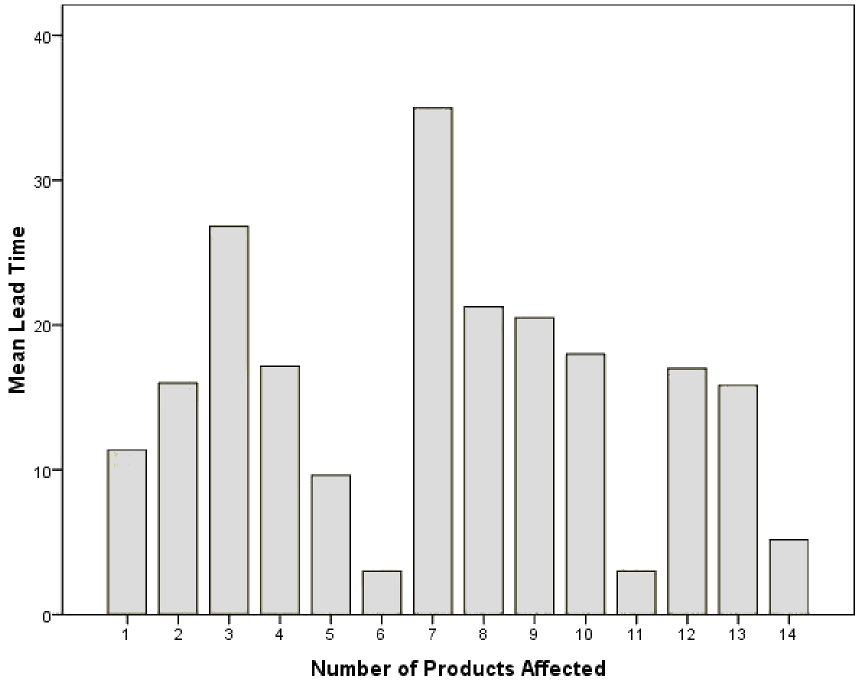


Fig. 4 Mean lead–time per number of products affected

take more time, which confirms the experiments reported by Hogarth (1975) 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 the 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 4):

H^2_0: 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^2_1: 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 4). 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 3, 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 factors 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 issues a request on the decision lead–time, we categorized the decisions in the decision log 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 extrenal 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 4):

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 (Wohlin et al 2000) results ($t(752) = .586, p = .558$, see the sixth row in Table 4) does not allow us to reject H_0^5. 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 the all decision 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 intepretation of this result may be that the case company does not pay enough attention to the requests of important customers and thus their lead-time is not shorter. If that is the case, introducing prioritization of change requests may be a possible workarounds.

The result of the survey (see Table 3) shows a negative relationship (requests issued by important customers have shorter lead-times), in contrast to the statistical analysis indicating no relationship, see fourth row in Table 4. Moreover, 62.8% of the respondents reported that time to make the decision is shorter when the decision is filled 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 confronted the results from the hypotheses testing with the results from the survey, see Tables 4 and 5.

Table 5 Survey results - the influence of decision characteristics on the decision outcome, research question RQ2 and survey question 9 (Wnuk 2012))

	This increase the probability of rejection	No influence	This decrease the probability of rejection	Rating average / Median
There are a high number of products affected by the decision, H^4	**54.8%**	33.3%	11.9%	-0.43 / -1
The decision is late in the release cycle, H^5	**71.4%**	26.2%	2.4%	-0.69 / -1
The decision is filled by an important customer, H^6	9.5 %	7.1%	**83.3%** (35%)	0.74 / -1
The decision took a long time to make, H^7	26.2%	**57.1%**	16.7%	-0.10 / -1

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 4), we have formed the following hypothesis:

H^4_0: The number of products affected by a decision is **not** different for the different decision outcomes.
H^4_1: 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 (Smirnov 1939) to test the relationship between an ordinal level variable and a nominal level variable. 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^4_0 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 5, 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 potentialy more promissing 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. (2009) reported five main reasons for excluding a feature candidate from the scope of the project but not analyzed the complexity of these feature candidates. 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 4) and confronted the results with the results from the survey, see the third row in Table 5:

H_0^5: The release number a decision affects is **not** different for the different decision outcomes.
H_1^5: 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 4). This result is above the documented critical value of Kolmogorov-Smirnov's Z, what means we can reject H_0^5 and accept the alternative hypothesis H_1^5. Thus, we can state that the changes 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 5. 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 2009, 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 the same.

5.4.3 Effect of Important Customers on the decision outcome: H^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 χ^2 test for $r * c$ tables.

Our hypothesis (H^6 in Table 4) is:

H_0^6: The frequencies in the contingency table between the decision outcome and involvement of important customers do **not** differ from the normal expected frequencies.
H_1^6: 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_0^6 and accept our alternative hypothesis. Since the value of χ^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 external customers than internal customers.

The majority of the survey respondents (83.3%, see row 3 in Table 5) 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 χ^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^2 and the decision outcome H^5 are not consistent, which could suggest additional uncovered factors. 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 4):

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 4) indicated a significant differences between the average lead–time for both decision outcomes. This means we can accept H^7_1 and reject the null–hypothesis H^7_0. 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 5, 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 4) which prevents us from drawing stong 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 faster 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. (2009), 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 Conclusions

Although RE decision making has been studies in a number of publications (Alenljung and Persson 2008, Aurum and Wohlin 2003, Barney et al 2008, Berander and Andrews 2005, Evans et al 1997, Fogelstrom et al 2009, Ngo-The and Ruhe 2005, Rolland et al 1995, Wohlin and Aurum 2005), little empirical evidence exists that explicitly and exhaustively investigates the relationships between the change requests attribute and the decision lead–times and outcomes.

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 confronted 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 (hypothesis H^1).
- The statistical analysis showed that if a request affects a lot of products, it has a higher change of being accepted (hypothesis H^4). 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.
- 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 (hypothesis H^2).
- Change requests affecting late releases have a significantly higher probability of acceptance according to the statistical analysis of the decision log (hypothesis H^5). 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.
- The lead–time for decisions is shorter when the change requests are issued by important customers, according to the respondents (hypothesis H^3). The statistical analysis of the decision log disproved this suggestion. Therefore, no clear relationship was identified for this factor.
- Change requests issued by important customers are more likely to be accepted, (hypothesis H^6) 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 (research question 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 decision take more time, it may be wise to decrease their complexity for faster 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 decision log 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 deicision 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.

Related to the differences observed between the statistical analysis results and the survey results, we report that there are premises that less complex decisions are more often rejected in large projects but not in smaller projects. Moreover, for smaller project the decisions affecting products planned to be released late in the release cycle are more likely to be rejected than for larger projects. At the same time, the majority of the survey respondent reported that time to make a decision is shorter when this decision is filled by an important customer, while for the large case company this relationship doesn't seem to hold.

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.

Finally, 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.

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 VINNOVA within the UPITER project.

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A APPENDIX: QUESTIONNAIRE QUESTIONS

B INTRODUTION

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 asses 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!

C 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)

D 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

	This makes the time to decide shorter	No influence	This makes the time to decide longer
There are a high number of products affected by the decision	( )	( )	( )
The decision is late in the release cycle	( )	( )	( )
The decision is filed by an important customer	( )	( )	( )

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

	This increase the probability of rejection	No influence	This decrease the probability of rejection
There are a high number of products affected by the decision	( )	( )	( )
The decision is late in the release cycle	( )	( )	( )
The decision is filed by an important customer	( )	( )	( )
The decision took a long time to make	( )	( )	( )