What Decision Characteristics Influence Decision Making in Market-Driven Large-Scale Software Product Line Development?

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Abstract. Time efficiency is crucial for decision making in large scale market driven software product line development. 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. A large requirements engineering decision log was used to statistically test all hypotheses. The results show that the number of products affected by a decision has a positive relationship with the time needed to take a decision. Furthermore, more products imply a longer decision lead time. Results also show that when a change request originates from an important customer, the request is sooner accepted than changes requested internally. For efficient requirements management, our findings support that decision making activities can be carefully refined in large scale requirements engineering processes. Our findings, may be useful for Product Managers to understand the consequences of making certain types of decisions and planning actions in order to avoid their negative effects.

Keywords: Requirements Engineering; Decision Making; Market Driven Development; Software Product Lines;

1 Introduction

Requirements engineering is accepted as one of the most crucial stages in software design and development as it addresses the critical problem of designing the right software for the customer [3]. This critical problem gains even more importance in the Market-Driven Requirements Engineering mode, where the product content has to be aligned with the need of the targeted market segments, often estimated to thousands or millions of potential users, in order to create a profitable software product [24]. In order to decrease the cost and increase the ability to provide an individualized software product, the concept of $\mathbf{2}$

software platforms in combination with mass customization is often used [22]. This concept, called Software Product Lines [22] allows software development organizations to reuse a common base of the technology and, at the same time, to bring out products in close accordance with customers' wishes. The inevitable cost for a greater degree of reuse and increased productivity is an increased complexity of coexisting product variants and a more complex decision making process. In this complex environment, deciding which requirements to include into the scope of an upcoming project is not a trivial task. Moreover, the effects of certain scoping decisions may severely impede the quality of software products, for example when accepting significant changes to the product line late in the process as late changes usually require substantial effort to be held and have higher impact on the quality of products. On the other hand, time is a scarce resource in every business, so knowing exactly how much of this resource is needed for a certain decision or project is decisive [18]. As a result, the selection process may turn out to be a complex decision problem, where often sufficiently supportive techniques for assisting in this process based on cost-value approach. like for example prioritization [15], have to be extended to additional factors. What actually are these 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, we performed a retrospective analysis of the decision making process in a large-scale product line project with the aim of identifying which characteristics of changes may influence the decision lead time and the decision outcome. Our results can support software product managers in knowing which consequences are of certain characteristics of a decision. When a product manager is aware of certain consequences he can take adequate actions in order to avoid negative effects and by that contribute to the improvement of the requirements management process within the company.

Decision making is an important aspect of requirements engineering, which by some researchers is provocatively put in the center of the field [1, 2, 10]. A number of challenges in the requirements engineering decision-making (REDM) field has been defined [1, 16], stressing the need to understand which factors affect requirements engineering decision makers. Furthermore, the need for empirical studies of REDM has been stressed [2, 21, 1]. The distinction between diagnosis and look-ahead ways of supporting decision making is proposed by Pomerol [23], who focuses on supporting look-ahead decision making. Various techniques, even as advanced as the Constraint Satisfaction Problem Solution Techniques [9] have been proposed to automatically reduce the space of choices for ambiguities, for example in the software design decision process. The problem of selecting right requirements to the next project or product release has been described or addressed in a number of studies. Among them, Karlsson [15] promotes a costvalue approach to support this activity, later experimentally compared to other prioritization techniques [17]. Wohlin and Aurum [29] investigated the reasons for including features, while Wnuk et al. [28] investigated the reasons for excluding features from the scope of the project. The investigation of REDM in large scale bespoke development performed by Alenljung and Persson [1] confirms our viewpoint of a large number of related aspects and dimensions of REDM that have to be considered in order to grasp its full complexity.

The paper is structured as follows. A description of the case company is given in Section 2. Our research design can be found in Section 3, together with the research questions in Section 3.2. After this, the statistical analysis of the decision logs will take place (Section 4), followed by the results (Section 5). The paper is ended by the conclusion and future research in Section 6.

2 Case Company Description

The results from the content analysis part of this paper are based on empirical data from an industrial project at a large company that is using a product line approach [22]. The company has more than 5000 employees and develops embedded systems for a global market. There are several consecutive releases of the platform, a common code base of the product line, where 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 launched with different platform releases. The company uses a stage-gate model with several increments [5]. The scope of the release project is constantly changing during this process, from the initial roadmap extraction which is a basic for creating high level features to the final milestone of the requirements management process after which the development phase starts. In this case, the project management makes scoping decisions based on groups of requirements that constitute new functionality enhancements to the platform, called features. Change requests to these features are performed constantly by stakeholder from inside and outside the company. The scope of each project is maintained in a document called the Feature List, that is regularly updated each week after a meeting of the Change Control Board (CCB). The CCB exists of a permanent group 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 changes that happen.

Each change request to the scope of the project within the case company is registered in the CCB decision log. 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, the decision date, the products impacted by a change, the release of the platform project impacted by a change, and the markets impacted by a change. For our research we were granted access to an extensive decision log with all data. The decision log of all products planned to be released in 2008 containing 1439 change requests was used as input for the content analysis presented in Section 4. 4

In the case company, a change request is filed after which, among others, ambiguity and completeness of the request are analyzed. This analysis is based on the Quality Gateway described by Natt och Dag et al.[19]. 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 in order to perform the Impact Analysis (IA). An IA is performed by the appropriate Technical Groups (TGs) that elicit and specify high-level requirements for a special technical area, and Focus Groups (FGs) that design and develop previously defined functionality. After the IA the request is presented at a CCB meeting and the change request is decided upon. When an 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. For an overview of the process see Figure 1



Fig. 1: CCB Decision Outline

Table 1: Decision Log Entry Example

3 Research Design

In this section we will explain how we defined our variables and how the hypotheses and research questions are constructed.

3.1 Variables

The research we performed was mainly exploratory and done in order to first identify the main characteristics of decisions in REDM and second analyze the relationships among these characteristics. After identifying the characteristics, we formulated research questions about relations within REDM and constructed our hypotheses based on these questions. We performed the appropriate statistical tests on the data from the decision log to either accept or reject all hypotheses and draw conclusions based on these test results. Based on the decision characteristics, 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 by a small difference in days between two decisions who took the same number of working days to be taken, due to the weekend. As an example, 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 indicating the number of different products for which the requirements would change if the request was accepted.

3. Release Heartbeat: a variable strongly related to the release method used within the case company. As described in section 2, the product line platform of the case company is released in a heartbeat rhythm of one base release and four sequential releases. The release heartbeat 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. 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 very large partners of the case company who also help to bring the developed products to the market.

5. Decision Outcome: This variable indicates whether or not a change request is accepted by the CCB, it is also of nominal level of measurement.

3.2 Research Questions

Seven questions have been posed in this study in order to determine the relationship among different decision characteristics in requirements engineering decision making. According to Easterbrook et al. [8], in general all of these question are of the form "Are characteristic X and Y related?". All research questions are tested with a specific hypothesis that is, if possible, based on previous scientific work.

The first question (H^1) "Is the lead time related to the number of products affected" is based on Hogarth [13], who created a function on the relationship between the decision time and the task complexity. Hogarth states, based on mathematical models he created, that the amount of time needed to take a decision is an increasing function of the task complexity, till a certain point. After some point the costs of errors due to the task complexity becomes lower than the cost of time.

The question whether (H^2) the decision outcome is related to the number of products affected by a decision is also based on the work of Hogarth [13]. Since there is a tilting point in the relationship curve, there is a certain level of complexity, after which the decision maker decides the costs of errors due to a wrong decision are lower than the costs of spending any more time an making the decision.

Question three (H^3) concerning the relationship between the specific release heartbeat and the decision time and four (H^4) concerning the release and the decision outcome are partly based on the work of Saliu and Ruhe [25] and the work of Bagnall et al. [4], in which they suggest a relationship between decision outcomes and release planning. No explicit relationship between decision lead time or decision outcome and the release in a release cycle is claimed, but we expect to find such a relationship in our data.

Hallowell [12] empirically proved a relationship among customer satisfaction, loyalty and profitability. Because of this relationship, we believe it is reasonable to assume there is the possibility there is also a (H^6) relationship between the fact a request is filed by an important customer and the decision outcome. The case company benefits of keeping the customer satisfied and could because of this sooner accept requests of this customer than internal requests. The same reasoning goes for (H^5) the relationship between a request filed by an important customer and the decision lead time.

The last hypothesis formulated (H^7) is based on the work of Zur [30], in which he empirically proves a relationship between the time pressure people experience and the risks of their choice behavior. All these questions will be analyzed statistically in the next section.

4 Results

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4.1 Test Selection

In order to perform parametric tests on the CCB decision log, all ratio level data should be distributed normally [11]. 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 D'Agostino-Pearson test [6] was used to see whether the log_{10} -function of the variable "Lead Time" described a Gaussian curve, or was distributed differently. With the D'Agostino-Pearson test we can test the following hypotheses (H^0) :

$H_{0[1]}^{0}$: The sample is [not] derived from a normally distributed population.

When testing the kurtosis and skewness [7] 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.

4.2 Effect of Number of Products Affected

We have two major hypotheses about the relationship of the number of products a decision affects. with other variables. The first hypothesis (H^1) on the relationship with the lead time of a decision can be described as:

$H^1_{0[1]}$: The correlation between the number of products affected by a

decision and the lead time needed to take the decision is [not] 0.

Since we will analyze a possible relation between a variable of ration level of measurement and one of ordinal level of measurement, we used the nonparametric Spearman's Rank-Order Correlation Coefficient [27] to asses the correlation size. 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 H_0 and accept the hypothesis that the correlation between the number of affected products and the lead time is not 0.

The second hypothesis (H^2) we tested related to the number of products affected by a decision can be described as:

$H^2_{[0]1}$: The number of products affected by a decision is [not] different

for the different decision outcomes.

Because the relationship between a variable of ordinal level and a variable of nominal level is tested, we use the Kolmogorov-Smirnov test for two independent samples [26]. 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 and accept our alternative hypothesis.

4.3 Effect of a certain Release

To test the effect of a certain release, we have stated two hypotheses. The first hypothesis about the effect of a certain release on the lead time of a decision (H^3) is as follows:

$H^3_{0[1]}$: The correlation between the specific release heartbeat and the

lead time needed to take the decision is [not] 0.

To test this hypothesis about the correlation between a variable of ordinal level and a variable of ratio level, we used Spearman's Rank-Order Correlation Coefficient. 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. This means we can not reject H_0 and we can not conclude there is any correlation between the release and the lead time needed to take a decision.

We also tested the relation between the release a decision affects and the decision outcome. We stated the following hypothesis (H^4) :

 $H^4_{[0]1}$: The specific release heartbeat a decision affects is [not] different for the different decision outcomes.

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We used the Kolmogorov-Smirnov test for two independent samples for this analysis, which resulted in a score of Z = 2.566, p < 0.01. This result is well above the documented critical value of Kolmogorov-Smirnov's Z, what means we can reject H_0 and accept the alternative hypothesis H_1 .

4.4 Effect of Large Customers

In this case, we first tested the difference of lead time needed to take decisions when large customers are involved in comparison with decision where they are not involved. In order to test this, we did a independent sample t-test on the following hypothesis (H^5) :

$H_{[0]1}^5$: The average lead time needed to take a decision is [not] different

when a large customer is involved.

The result of the t-test (t(752) = .586, p = .558) did not allow us to reject H_0 , 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 a large customer, compared with a decision that is requested from within the company.

We also tested if there was any effect on the decision outcome caused by large customers. In order to test this we had to perform a χ^2 test for r * c tables, because we tested the relation between two variables of nominal level of measurement. Our hypothesis (H^6) is:

$H_{[0]1}^6$: The frequencies in the contingency table between the decision outcome and involvement of a large customer do [not] 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 and accept our alternative hypothesis. Since the value of χ^2 is rather low, we can state that the change of a positive decision outcome is with large likelihood a little higher when a decision is requested by a large customer.

4.5 Effect of Lead Time

In order to test whether the lead time influences the acceptance rate we stated the following hypothesis (H^7) :

$H^7_{[0]1}$: The average lead time needed to take a decision does [not] differ

per decision outcome (i.e. accepted or rejected).

The average lead time for rejected and accepted decisions is respectively $\mu = 1.12$ and $\mu = .98$. The result of the t-test (t(752) = 3.940, p < 0.01) indicated a significant differences between the average lead time for both decision outcomes. This means we can accept H_1 and reject the null-hypothesis.

5 Interpretation of Results

From the results presented in Section 4.2 we can see a significant relationship between the number of products affected by a decision and both the decision lead time (H^1) and outcome (H^2) . Our results of testing on a large dataset can be interpreted as empirically confirming claims of Hogarth et al. [13], who state that the time needed to take a decision is highly dependent on the task complexity, in our case represented as number of products. To support out interpretation we have analyzed number of products involved in the decision and the decision lead time.



Fig. 2: Mean Lead Time per Number of Products Affected

is a positive trend to be seen.



Fig. 3: Percentage of Accepted Decisions per Customer Type

Figure 2 shows an increase of the average lead time related to the number of products. If we compare the average lead time for 1 product with the highest lead time (for 7 products), the lead time becomes about five times longer. If we look at a more realistic comparison of lead time between the lead time for 1 product and 13 products we can still see an increase of 130% in average lead time. However, there appears to be no clear function to predict the amount of time needed to take a decision when the number of products is known, but there

Other research [25, 4] also suggested a possible relationship between release planning and decision quality. This relationship could only partly be found in our case data, since there proved to be no significant relationship between the release a decision affects and the lead time (see Section 4.3). We did find a significant relationship between the release and the decision outcome (see Section 4.3), meaning decisions either get accepted or rejected more when the case company is later in their release cycle (H^4) .

The fact that a request is filed by an important customers has no relationship with the decision lead time (see Section 4.4). It does however have a relationship with the decision outcome. Request filed by an important customer or more easily accepted than request coming from inside the company (H^6) . We have further analyzed this result by analyzing the percentage of accepted decision per customer type. The results are depicted in Figure 3, where we can see an 11% difference between the two groups. Expecting a higher acceptance rate on internal requests, because of an expected higher accuracy of internal requests, this relationship is remarkable.

The final result of our statistical analysis shows a significant relationship between the lead time and the decision outcome. This means that the decision outcome could be influenced by the time needed to take a decision. This implication could be of high relevance because it could mean that more wrong decisions are made in decision procedures that take a long time.

6 Conclusion and Future Work

Software Product Line scoping is a complex task, which includes analyzing many dependencies between customers and products derived from the product line in order to find an optimal set of features for a certain release. In Market-Driven SPL, the number of decision aspects that have to be taken under consideration and their dependencies grows significantly. In order to effectively improve RE decision-making we have to identify the key aspects of this process [1, 20]. Furthermore, the quality of decisions taken while deciding about the scope of the next release of software products directly influences the quality of the requirements for this release [1]. This in turn may improve the overall quality of software products.

In this paper, we performed a retrospective analysis of the decision making process in a large-scale product line project with the aim of identifying which characteristics of changes may influence the decision lead time and the decision outcome. Based on our case study statistical analysis, we can conclude that:

- There is a relationship between both the number of products affected in a decision and the time needed to take a decision and decision outcome. Our conclusion here is that decisions are sooner accepted when they have a large number of products they affect, than when they affect a lower number.
- Change requests done by an external customer are more likely to be accepted than internal request. Requests filed by an important customer have an 11% higher change to be accepted than other requests.

Our results provide valuable information for project manager that can be used to estimate the decision lead time for complex changes. In our case, the lead time turned out to be up to 400% longer if a decision affect multiple products. The fact that changes submitted by external customers are more likely to be accepted has two sides; on one hand it can be positive since Hallowell [12] and Kabbedijk et al. [14] both stated the importance of listening to customers in order to get their satisfaction and loyalty. On the other hand, this effect could also mean that change request filed by an important customer are only accepted to satisfy this customer and not because it is a useful change to the product. Product management processes can be adapted when being aware of the supported relationships. Future research is needed to go more in depth on the possible relationships among REDM characteristics. Two relationships could be proven and quantified by us, based on the dataset, but the other five relationships need further research in order to further validate them. Within the two relationships proven by us, more research is needed as well. For instance, it would be helpful 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, could also be of relevance for the decision lead time or outcome.

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