



**DATA ANALYSIS ON THE EFFECTS OF ADOPTING
A NEW AGILE-BASED INFORMATION TECHNOLOGY
OPERATING MODEL**

Lappeenranta-Lahti University of Technology LUT

Master's Program in Computational Engineering, Master's Thesis

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ABSTRACT

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Data analysis on the effects of adopting a new agile-based information technology operating model

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KONE IT adopted a new information technology (IT) operating model over the years 2023 and 2024. This new operating model included a change to ways of working targeting IT product management. The new operating model adopted methods from agile methodology, product management and DevOps. The purpose of the change was to create a unified and efficient IT product management methodology, which would in return improve employee working efficiency and satisfaction. The adoption process was monitored using a self-assessment form where product owners followed their products' adoption maturity to each of the new methods. At the end of the adoption phase, feedback of the adoption process was gathered from the IT product management teams. The self-assessment results were then analyzed together with work monitoring data and the feedback survey data. The methods used were correlation analysis, principal component analysis and K-means clustering along with visual analysis tools such as heatmaps, Venn diagrams and other plots. The result of the analysis was that there were no immediate identifiable benefits from the adoption of the new working methods included in the operating model change. Improvement suggestions were given to the company based on the insights and results from the study.

TIIVISTELMÄ

Lappeenrannan-Lahden teknillinen yliopisto LUT
School of Engineering Science
Laskennallinen tekniikka

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Ketterän informaatioteknologian toimintamallin käyttöönoton vaikutusten data-analyysi

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Hakusanat: Data-analyysi, business-analyysi, pääkomponenttianalyysi, K-means, korrelaatioanalyysi, ketterät menetelmät, DevOps, IT-tuotteiden hallinta, toimintamalli, muutoshallinta

KONE IT otti käyttöön uuden informaatioteknologian (IT) toimintamallin vuosien 2023 ja 2024 aikana. Yhtenä osa-alueena uudessa toimintamallissa olivat muutokset työskentelytapoihin IT-tuotteiden hallinnassa. Tässä uudessa mallissa otettiin käyttöön työskentelymenetelmiä ketterästä ohjelmistokehityksestä, IT-tuotehallinnasta ja DevOpsista. Muutoksen tarkoituksena oli luoda yhtenäinen ja tehokas IT-tuotteiden hallintametodologia, joka parantaisi työntekijöiden tehokkuutta ja työtyytyväisyyttä. Käyttöönoton etenemistä seurattiin itsearviointilomakkeen avulla, johon IT-tuotteiden omistajat merkitsivät käyttöönotettujen metodien kypsyyttä jokaiselle IT-tuotteelle. Kun käyttöönottoprosessi oli saatu päätökseen, työntekijöiltä kerättiin lisäksi palautetta koko prosessista. Itsearviointilomakkeen dataa analysoitiin työnteon seurantadatan ja palautekyselyn kanssa. Tutkimusmetodeina käytettiin korrelaatioanalyysia, pääkomponenttianalyysia, K-means -ryhmittelyä sekä muita visuaalisia työkaluja ja kuvaajia. Analyysin perusteella havaittiin, että uudet työskentelymenetelmät eivät tuottaneet huomattavia parannuksia työnteeseen. Yritykselle annettiin tutkimuksessa tehtyjen löydösten ja tulosten perusteella parannusehdotuksia.

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Although I am sad to see the program now being removed I am grateful that I had the opportunity to study under the Business Analytics program of the Computational Engineering Department. I firmly believe it to have been the best combination of mathematical, scientific, technological and industrial studies anywhere in Finland. (Or at least that's my opinion ;)

Finally, I thank my family for being extremely supportive and helping me with arranging my life outside of Lappeenranta.

Also, I would like to state that **no AI tools were used in this project.**

Lappeenranta, June 13, 2025

Anton Valdemar Helminen

LIST OF ABBREVIATIONS

| | |
|--------|------------------------------|
| ANOVA | Analysis of Variance |
| COTS | Commercial-off-the-shelf |
| DevOps | Development Operations |
| IT | Information Technology |
| PaaS | Platform as a Service |
| PC | Principal Component |
| PCA | Principal Component Analysis |
| SaaS | Software as a Service |
| SVD | Singular Value Decomposition |

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Appendix 1: Adopted ways of working

Appendix 2: Adopted working processes

1 INTRODUCTION

1.1 Background

As the modern software and hardware becomes more and more complicated by the day, developers and Information Technology (IT) product managers require more effective ways of working and new tools to keep up with the demands of multiple stakeholders. Some techniques to improve these development routines are agile methods [1], Development Operations (DevOps) [2] as well as software product management guidelines and tools [3].

KONE IT, the organization responsible for managing the various software and hardware IT products at KONE Oyj, adopted a new IT operating model over 2023 and 2024. The new operating model included changes to ways of working and working processes, including methods from agile, DevOps and product management. The goal was to improve the performance and work experience of IT product management employees in KONE IT.

Implementing all of these methods in an organization should, in theory, be a very useful and profitable process, since the ultimate purpose of these tools and guidelines is to improve efficiency and make the working life of employees easier. However, like with adopting any new methods into an organization, proper change management is necessary for the adoption process to be successful. In the past, adoption of multiple methods simultaneously has been found to not necessarily produce benefits for an organization [4]. Therefore, the adoption process needs to be planned and executed properly.

1.2 New information technology operating model

In KONE IT, IT products are managed by individual product owners. The hierarchy can be described as a layered structure where on the bottom are all of the individual IT products which consist of either one or more software or hardware applications. IT products are combined under product groups, which are combinations of products that share similar functions and capabilities. These product groups are managed by product group managers which operate under the five different departments of KONE IT. The hierarchy of products is shown in Figure 1.

KONE IT adopted a new IT operating model in 2024 starting at the end of 2023. The

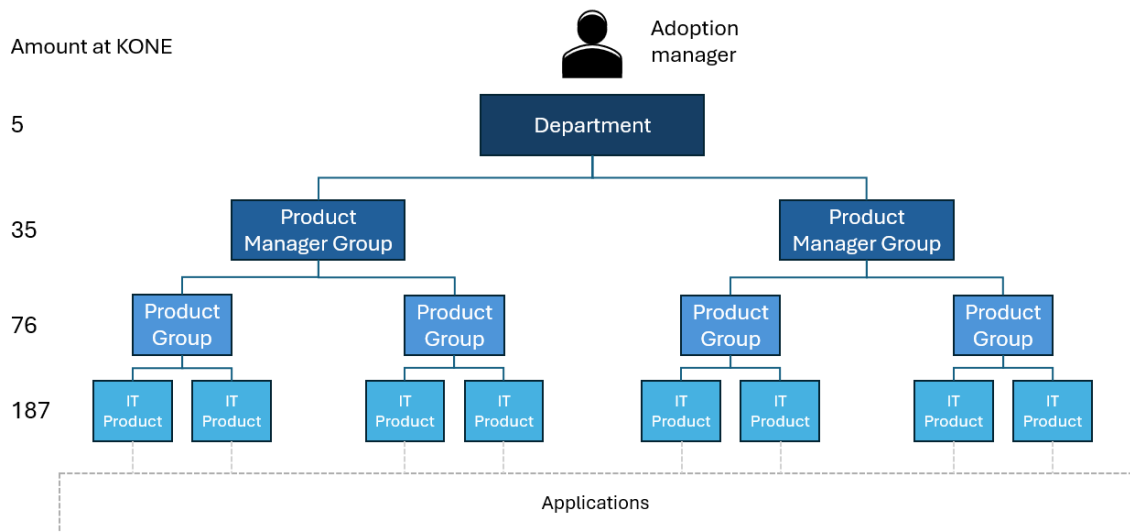


Figure 1. IT product hierarchy at KONE. There were a total of 5 different departments which each had their own IT products. Each department had one adoption manager who was responsible for overseeing and assisting in the adoption process.

model included a number of changes to ways of working utilizing agile methods, product management techniques and DevOps. As seen in Figure 1, one adoption manager was assigned to each of the five departments in IT to manage and monitor the adoption process. A total of 187 IT products and their management personnel were affected by this change process. Overall 81 ways of working methods and work processes were included in the adoption. The level of made adoption progress was measured with a self-assessment form over the year and monitored by the adoption managers.

The assessment form contained each of the 81 methods (See Appendices 1 and 2) and they were rated on a score of 0-5 or not applicable (NA) for each of the products. This value is called the maturity of a method for each IT product and it describes the overall level of adoption. Calculating the average of all the maturity values for the methods adopted by a product gives us the maturity value for that specific product. The goal for the year 2024 was to get all of the IT products to an overall average maturity level of 3 or above. This could be accomplished by giving proper training and guidance in adopting these new ways of working.

The evaluation results were recorded twice during the year; first time was after the first half (H1) at the end of June 2024 and the second time was at the end of the second half (H2) at the end of December 2024. The second evaluation was the final evaluation and it is used as the dataset for analysis in this project.

1.3 Objectives and delimitations

The goal of this thesis is to explore the adoption process of the new IT operating model as well as study the impact it had on employee working efficiency as well as satisfaction. This is done by conducting a data analysis aiming to:

- Explore the adoption process and result using clustering.
- Study the correlation between the made maturity progress and productivity and employee satisfaction metrics.
- Examine the feedback given by employees.

This way the objective of the thesis can be split into a four concise research questions:

1. What was the adoption maturity of the teams after the adoption process?
2. How does the adoption process go for different teams?
3. Is there a noticeable correlation between the adoption maturity and the performance and satisfaction of employees?
4. If the adopted methods are not showing improvement, what are the reasons and what could be done differently?

1.4 Structure of the thesis

This thesis consists of six main chapters in addition to the introduction. Agile methodologies, DevOps and Product management tools as well as their previous studies and results are presented in Chapter 2. Used datasets are described in Chapter 3 along with some exploratory data analysis results. Chapter 4 explains the chosen analysis methods. This chapter has three sections for each of the used methods, principal component analysis, correlation analysis and K-means clustering. Performed analyses and their results are presented in Chapter 5 and discussion of the results in Chapter 6. Finally, conclusion of the entire project is given in Chapter 7.

2 RELATED WORK

In this chapter the different methods that are part of the operating model change are introduced, as well as previous study and analysis methods used to study them in the past. As mentioned in Chapter 1, the KONE IT operating model change introduced tenets from:

- Agile methods
- DevOps
- Product management ways of working

Methods from each of these are used for a slightly different purpose and may have both individual and overlapping impact on each other. As mentioned before in Section 1.2, there were 81 adopted methods in total.

2.1 Agile methodology

Agile methods are widely seen as the new way for software businesses to adapt into the modern development environment [1]. They are based mostly on the agile manifesto created in 2001 [5] by a group of agile enthusiasts. They wished to renew the old software development procedures by replacing a strict rule- and hierarchy-based development with a more flexible and 'agile' set of methods.

The agile methods have been adopted in multiple IT industries with a hope of gaining return for investment, improving working speed and quality and increasing flexibility over projects [6]. Despite seeming to function on paper, there seems to be a division in people's opinion on whether the agile methodology actually delivers what it promises. Also, there appears to be a lack of data-driven empirical studies on the effects of adopting agile methods. This point was suggested by another empirical study made by Mishra et al. in 2021 [7].

Before, agile methods and their impact has been studied both qualitatively as well as quantitatively [4]. Often in these cases the method of approach has been interviewing people and their personal success of applying agile methods in their work or projects. In one quantitative study [8], the approach was to send out quizzes to various project managers and have them fill out their perceived success in completing projects while using agile versus traditional waterfall models. The method of analysis was usually a

correlation study while utilizing regression methods or Analysis of Variance (ANOVA). The result for this study was that the projects that utilized agile methods had a higher success rate than the projects that did not.

Overall, there has been a relatively low number of studies related to the effects of agile methods. As seen from Figure 2, the total amount of scientific articles published per year has been steadily increasing, but there has only been only around 15 articles per year from the last 10 years. These results were obtained from Scopus using the search words "agile methods" AND "effects". Although the search words may not find all articles and studies, it does show that the amount of articles related to the study of agile method effects is also low. Therefore there is a reason to study the effects of agile methods more from a data centric perspective.

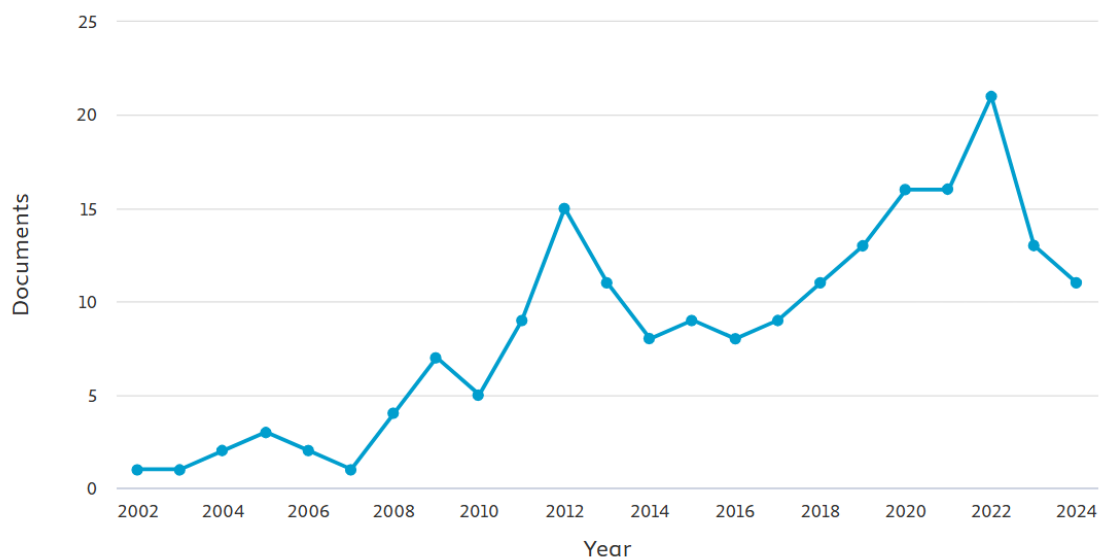


Figure 2. Amount of scientific documents created related to the study of effects of adopting agile methods. Source: Scopus

2.2 DevOps

DevOps is a combination of development (Dev) tools and operations (Ops) that aim to automate and speed up testing and deployment of software [2]. It is commonly used for software development. In its core, DevOps means utilizing automated workflows and cloud-based infrastructure to integrate testing and development of software. It also includes a set of non-technical ways of working changes, which aim to combine both development and operations teams into a one end-to-end team. This is done so that no handovers from

development to operations is needed and operations requirements would be taken into account in the development prioritization better. This requires teams to start using specially designed DevOps tools which include continuous-integration, deployment, logging and monitoring tools [2].

Because of the requirement to learn new tools and ways of working, such as agile methods, adoption of DevOps can be a major cultural and organizational shift. It requires proper change management and integration from the company's side in order to fully adopt DevOps as part of development routines. Like mentioned in [9], a study conducted in 2016, the challenges around adopting DevOps practices are mostly centered around communication and understanding the need for change. Lack of understanding the need and purpose of the tools can potentially cause users to misuse the tools and interpret their purpose differently from intended. This in turn can cause the tools not being used optimally which can cause suboptimal results.

In [9] it was also mentioned that there are clear benefits to successful implementation of DevOps. Most common benefits were improved quality, enhanced collaboration and improved well-being of the DevOps teams. It is worth to note that this study, like many others, was conducted only as a survey, meaning no other data, besides what was told by people, was used to back up the results. Therefore, it would be beneficial to validate these results with additional data analysis.

2.3 Product management

Most companies use both internal and external software and hardware products. Software products can be purchased as either licenses or online services used in daily operations such as Platform as a Service (PaaS), Software as a Service (SaaS) or Commercial-off-the-shelf (COTS) products. These software products are virtual goods which are purchased as one-time payments or they have running license costs [10]. Software made in-house is referred to as homegrown applications.

Both software and hardware products must be managed and their usage developed in order to make the most out of the investment. Software can also be developed internally, which also requires proper management and development protocols to ensure good quality software with efficient development speed [3]. It is the duty of product managers to make sure that proper principles are utilized in product management.

The core of product management is to manage the life-cycle and roadmap of a product as well as manage the required changes and adoptions of new management methods. In the end, responsibility of adopting agile methodologies and DevOps falls to the product manager.

Most product managers and product owners are often promoted from technical positions within the company. This means that they do not possess any formal training and therefore do not master their role initially [3]. Because of this, management styles and performance can vary within a company or organization with several product managers.

Like with agile methods, performance of product management can be somewhat difficult to evaluate. Still, it has been noticed that properly managed products can produce improvement in efficiency and cost management [3]. Effects of product management have been studied applying correlation analysis between projects and their success rates as well as speed [11]. The result was that the higher the product management level was, the better the perceived benefits were from project success perspective. Still the benefits could be studied further with more analytical methods and utilizing different data.

2.4 Data analysis methods

Effects of adopting new methods, like agile, can be carried out using data analysis methods. For example Principal Component Analysis (PCA) and K-means clustering have been used in the past for studying adoptions of different agile methodology groups [12]. For any data, it is also possible to use methods like correlation analysis [13] to explore relationships between variables. Both PCA and K-means clustering, in addition to correlation analysis, are all-around useful data analysis methods. These methods can be also used for studying the various datasets collected for this research.

The methodology should be chosen based on the available datasets, so there is no single predefined method for studying this type of operating model change. The datasets used in the work are described in Chapter 3 and they include mostly numerical values and variables which can be studied using the methods above. The datasets are different and include both survey data as well as externally monitored data in order to get more points of view on the adoption process. However, as most of the data used in this project is direct inputs from people in the form of self-assessment or survey, some considerations about the data and results should be taken.

2.4.1 Survey and self-assessment data analysis

Survey and self-assessment data are similar in nature, as both include evaluations provided by different people. Like any datasets, these can be studied using statistical methods [14]. Correlation as well as PCA analysis are applicable to studying relationships with other datasets. However, the methods and measurements used in the data collection process naturally have a large impact on the results of the analysis. Dataset size and bias are dependent on the number of respondents as well as where those responses come from. Regardless of the results, these factors should be taken into account when drawing conclusions from the data.

3 DATA COLLECTION AND CHARACTERISTICS

A total of four data sets were used together in the analysis:

- Adoption self-assessment data
- IT backlog management tool work monitoring and planning data
- Adoption feedback survey data
- Additional data of IT products

Datasets were retrieved as MS-Excel files, which were then combined and cleaned using PowerQuery and Python. Data from the IT backlog management tool had to be downloaded using a Python script utilizing an Application Programming Interface (API) connection.

3.1 Adoption self-assessment data

The first dataset is the self-assessment data collected from all of the IT products. Each of the IT products in KONE IT were assessed by evaluating the maturity of each agile, DevOps and product management method in regards on how it applied to the products. These assessments were completed individually by the product owners and their managers for each IT product.

There were a total of 187 products with each having a total of 81 different adopted methods covering agile, DevOps and product management. The methods were split in two groups: one covered methods related to ways of working and the other focused on improving work processes. The complete list of ways of working is in Appendix 1 and for processes the complete list is in Appendix 2. Out of the 187 products, 160 products were completely assessed. Only these fully completed assessments are included in the analysis and conclusions, since the incomplete ones lacked either all or majority of the method assessments.

Each assessment of a method was evaluated on the scale of 0-5 or NA (Not Applicable) with 0 representing the lowest level of maturity and 5 representing the highest. The statistics of this original assessment dataset are shown in Figure 3. The average of fully completed assessments was 3.01. Afterwards, in order to process NA values in PCA, these were replaced with value 0 in order to indicate no progress made in those areas.

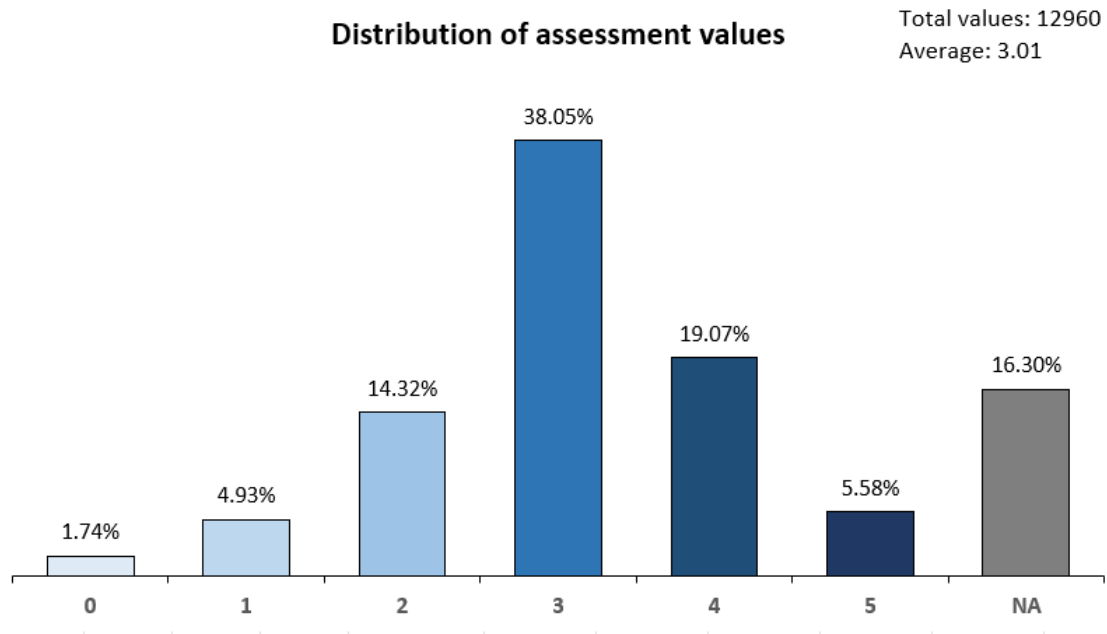


Figure 3. Distributions of assessment values for the entire KONE IT. Values are approximately normally distributed with 3 being the most common assessed grade.

KONE IT had specified that for the year 2024 the target average maturity was to be above 3, which was completed based on the overall average adoption maturity. However, as seen from Figure 4, not all departments reached that level. While all other departments managed to reach an average maturity of above 3, Department 4 had adoption maturity of only 2.8.

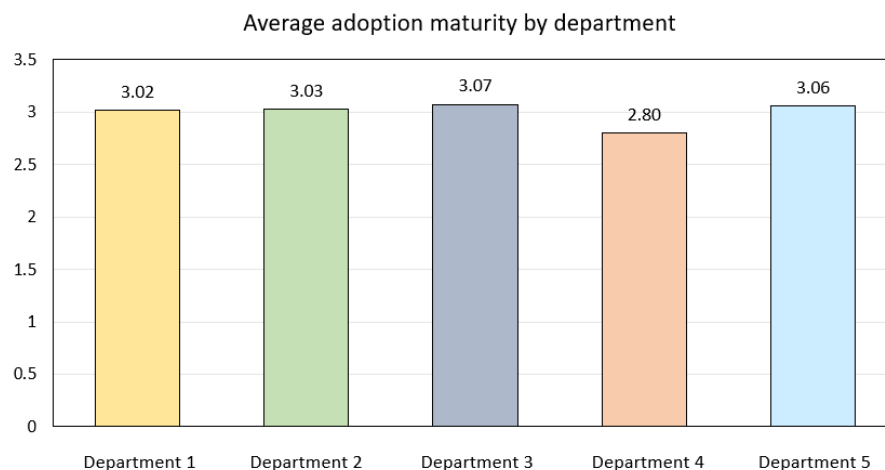


Figure 4. Average adoption maturities of each department in KONE IT. Although the average maturity for the entire KONE IT was above 3, the maturity levels vary between the departments. Department 4 is the only one below the target, having adoption maturity of 2.8.

3.2 IT backlog management tool work data

The second dataset came from a work backlog management tool used for work planning and issue monitoring. Each larger work task related to IT product management is also recorded there. The highest level work tasks are called initiatives, which can be split into epic sets comprised of Epics. Epics are further divided into smaller stories. This hierarchy is also shown in Figure 5. This project focuses on the analysis of story level work, since they are used in KONE IT as medium to small level work assignments and therefore there is a large number of them available for analysis.

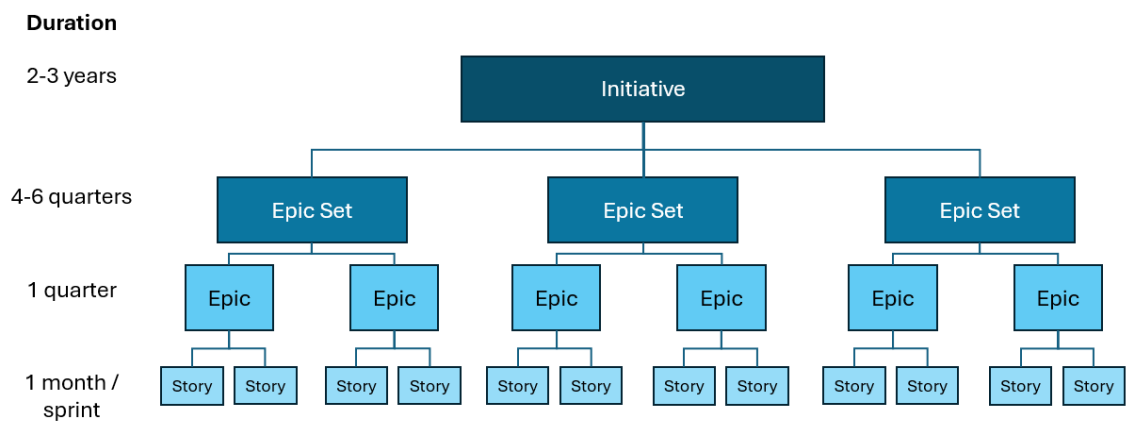


Figure 5. Hierarchy of the work tasks and their duration. Lowest level work is monitored as stories, which include the majority of work assignments and tasks at KONE IT.

This work dataset contained the amount of work tasks and their duration for every product manager. Both the amount of tasks and work duration were compared with the values from the previous year (2023) and the values were calculated as changes from the last year. The summary of this dataset is shown in Table 1.

Table 1. Story related data summary. There has been a slight overall improvement in amount and duration of stories completed over the year 2024.

| Work data statistic | Observations (rows) |
|--|----------------------------|
| Unique product owners | 72 |
| Average change in stories completed 2024 vs 2023 | 22.08 |
| Average story duration change 2024 vs 2023 | -57.99 days |

From the assessment data not all products contained work data found in the backlog management tool, so those were either dropped out of evaluation or grouped together with

other IT products. This left a total of 120 products with both work and assessment data.

3.3 Adoption feedback questionnaire data

The third dataset comes from a feedback survey sent to all the product owners, product team members, product designers as well as ops and technical leads. This totaled approximately 300 people. This survey had questions regarding how useful the adopted methods were perceived by the adopters themselves as well as questions to map the working satisfaction after the adoption process. The questions included in the feedback survey along with the answer formats are shown in Table 2.

Table 2. Feedback questions. There were a total of nine questions out which three were numeric values. These numeric values were used in statistical analysis in Chapter 5.

| Question | Answer options |
|---|--|
| What is your role? | (1 selection) Product owner / Product manager / Product designer / Technical designer / Operations lead / Other role |
| Which product group were you working with? | (1 selection) All KONE IT product groups |
| What were the most important categories of adoption in the new operating model? (2 options) | (2 selections) Agile ways of working / DevOps ways of working / Product mindset / Flow IT processes |
| How could the methods in these categories be improved? | Free-form text answer |
| How useful did you find the adopted methods? | Numeric answer 1-10 |
| What was your overall satisfaction with the adoption process? | Numeric answer 1-10 |
| How could the adoption process be improved? | Free-form text answer |
| How much time did it approximately take to complete the adoption in your product group? | (1 selection) 1-3 months / 4-6 months / 7-9 months / 10-12 months |
| In general, how satisfied are you with your role currently? | Numeric answer 1-10 |

The feedback was collected using Microsoft forms which was opened on in the beginning of 2025. Responses were collected until the end of march 2025 with the total number of respondents being 61 which means an approximate 20% survey response rate. There is also verbal feedback in the form of free-form text answers. The verbal feedback questions, as seen in Figure 2, were only about improvement points.

3.4 Additional data of IT products

In addition to the previous data sources, data of applications belonging to each IT product was available from an IT service management tool. This dataset contained product age and type information of business applications. As the information was only on application level, this data was then grouped under each IT product to compare with the assessment data. The information gained from this dataset on the product level is shown in Table 3.

Table 3. Additional IT product data gained from the IT service management tool.

| Variable | Calculation logic |
|-----------------|---|
| Product age | Average of a categorical value ranging from 0-6; 6 being oldest |
| Homegrown | Count of Homegrown (in-house) applications |
| SaaS/PaaS | Count of SaaS/PaaS applications |
| COTS | Count of COTS applications |

3.5 Utilization of the datasets

Data from both the work dataset as well as the feedback forms were combined with assessment form data to create response variables in order to statistically study dependencies between the assessment maturity values and employee performance and satisfaction. Additional IT product data was combined with the self-assessment data to inspect clusters in more detail. Detailed description of the experiments and the exact data usage in them is explained in detail in Chapter 5.

4 DATA ANALYSIS METHODS

Utilizing more than one method for the datasets in Chapter 3 should be useful for finding patterns as well as result validation. To study these datasets and in order to find useful insights from the data, I chose to use:

- Principal Component Analysis (PCA) for detailed correlation analysis and as a dimensionality reduction and data pre-processing method prior to clustering.
- K-means clustering and silhouette values to find and create optimal number of clusters to see how the adoption process might vary between different products.
- Correlation analysis on the dataset to see how the different adopted methods of the IT operating model (DevOps, Product management and agile) are correlated with response variables.

4.1 Principal Component Analysis

PCA is a linear dimensionality and noise removal technique where variables in the data are reduced to simplified principal components that aim to capture the variance of the underlying dataset [15]. Each Principal Component (PC) is a new vector made by combining representing the direction of variance of the original values.

PCA is based on the Singular Value Decomposition (SVD) which is defined as:

$$\mathbf{X} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T, \quad (1)$$

where \mathbf{X} is the data matrix, columns of \mathbf{U} are the left hand side singular vectors, columns of \mathbf{V} are the right singular vectors and the diagonal elements of $\mathbf{\Sigma}$ are the singular values. The formula for PCA can be derived from the definition of SVD:

$$\begin{aligned} \mathbf{P} &= \mathbf{V} \\ \mathbf{T} &= \mathbf{U}\mathbf{\Sigma} \\ \mathbf{X} &= \mathbf{TP}^T + \mathbf{E}, \end{aligned} \quad (2)$$

where \mathbf{X} is the data matrix, \mathbf{T} contains the object scores, \mathbf{P} is the matrix of loadings (eigenvectors) and \mathbf{E} is the residual matrix. The superscript T indicates transposition.

PCA can then be used to evaluate the contributions of different variables to the principal components and assess the effect of each variable to each other and how they are correlated with the response variables. The amount of PCs to use can be chosen utilizing a scree plot [15]. The scree plot shows the amount of explained variance per each individual PC as well as the cumulative explained variance. Usually the amount of PCs to use is chosen based on the explained cumulative variance. The threshold can be for example 90% or 95%.

The evaluation of correlation in PCA can be done using the loading vectors for each principal component. The loading values indicate correlation of the variables to the principal components, information which can be used to evaluate the correlation between the variables themselves as well. High positive loading values indicate positive correlation and negative loading values indicate negative correlation.

4.2 K-means Clustering

K-means is an unsupervised clustering method which groups similar data points together into so-called clusters [16]. The amount of clusters is defined by the parameter k in the K-means. These clusters can be then inspected to see if the data can be successfully separated to groups of similar data points. The pseudocode for K-means is presented in Algorithm 1.

Algorithm 1 K-means

Input: Data of observations

Output: cluster centroids + cluster assignments for each sample

1. Initialize k cluster centroid points randomly.
 2. For each data sample find the closest cluster centroid.
 3. Move each cluster centroid to the mean of the data points assigned to them.
 4. Continue steps 2 and 3 until cluster centroids no longer move.
-

To determine the optimal number of clusters to use for a specific dataset a silhouette approach [16] can be used. Silhouette index is a measure that represents the distance of a clustered data point to its assigned cluster center. Ground truth information on the groups

is not required, which means that it is best suited for a case such as this, where the target is to create clusters instead of classification.

Silhouette index is calculated for each data point as follows [16]:

$$s(x_i) = \frac{b(x_i) - a(x_i)}{\max\{b(x_i), a(x_i)\}}, \quad (3)$$

where s is the silhouette index, x_i is an element in a cluster and $a(x_i)$ is the average distance of x_i to all other elements within the same cluster. $b(x_i)$ is then defined as:

$$b(x_i) = \min\{d_l(x_i)\}, \quad (4)$$

where $d_l(x_i)$ is the average distance from x_i to all points in a cluster. The silhouette index values range from -1 to 1 where positive values indicating better fitted clusters. Negative values on the other hand indicate poorly fitted cluster centroids. Based on this silhouette index it is possible to estimate the optimal number of clusters for the K-means method by maximizing the average of silhouette index for all data points.

In the context of studying method adoption for different IT products, method adoption assessment values can be used as data for K-means. This way it is possible to see which IT products share a similar adoption pattern. These groups can then be inspected to determine adoption profiles of different products and their owners. When determining the optimal number of clusters based on silhouette values, it might be useful to select as few clusters as possible. This helps in directing attention to a few concise groups rather than focusing on multiple different groups individually.

4.3 Correlation analysis

Correlation analysis is a method of measuring the apparent dependence between variables. Correlation coefficient, R , measures the closeness of two variables [13]. This value can be calculated, for example, using Pearson's correlation coefficient, which is defined as:

$$\mathbf{R} = \frac{n(\sum xy) - (\sum x) \cdot (\sum y)}{\sqrt{n(\sum x^2) - (\sum x)^2} \cdot \sqrt{n(\sum y^2) - (\sum y)^2}}, \quad (5)$$

where n is the number of observations and x and y are the observations of two variables \mathbf{x} and \mathbf{y} respectively.

R gains values between -1 to 1 where values closer to -1 indicate negative correlation and values closer to 1 indicate positive correlation. Values close to zero indicate nonexistent correlation.

The data can be analyzed for correlation using a correlation matrix to see how the different variables behave in relation to each other. In a correlation matrix all variable's correlation coefficients are displayed together in a matrix form. An example of four variable correlation matrix is displayed in Figure 6.

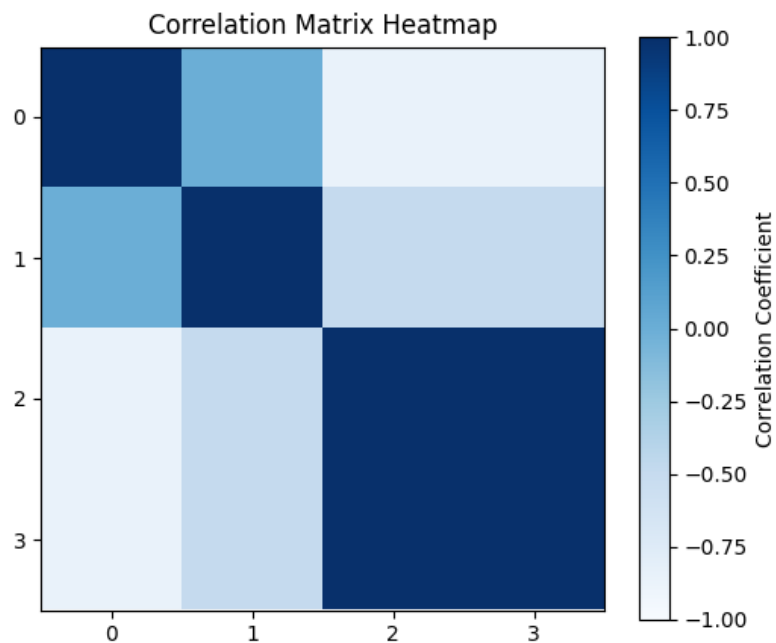


Figure 6. Correlation matrix example with four variables labeled 0-3. Dark blue indicates strong positive correlation while white indicates strong negative correlation. For example: variable 3 has strong positive correlation with variable 2 while variable 1 has weak (near 0) positive correlation with variable 0.

In a correlation matrix, the diagonal elements always have value of 1. This is because the variables are always perfectly correlated with themselves. In the correlation matrices found in Chapter 5 the correlation values are also displayed in the matrix for easier interpretation.

5 RESULTS

Almost all experiments and visualizations in this chapter were done using Python. All scientific algorithms presented in Chapter 4 were implemented using pre-existing python libraries and packages. Data management on Python's side was done using both Pandas dataframes and Numpy arrays. The complete list of Python libraries and their use cases is in Table 4.

Table 4. Python libraries used in experiments and their purpose.

| Python library | Usage |
|-----------------------|---|
| Pandas, Numpy | Data management |
| Matplotlib, Seaborn | Data visualization |
| scikit-learn | PCA, K-means, silhouette, min-max scaling |

In addition to this MS Excel was used for the more detailed feedback analysis and visualization in the last experiment.

5.1 Data normalization

Before clustering as well as before applying PCA, the data was scaled and centered using standard scaling technique, which is defined as:

$$X_{\text{scaled}} = \frac{X - \mu}{\sigma}, \quad (6)$$

where X is an individual data point, μ is the mean of all values in the entire dataset and σ is the standard deviation of all values in the dataset. This was done in order to bring the assessment data and the response variables to the same scale.

5.2 Results

Results for each of the described experiments are displayed in this chapter. Each plot, table and graph is commented and for each experiment, applied preprocessing and justification is explained more in detail.

5.2.1 Clustering analysis of adoption patterns

Clustering was used to examine the adoption process across the different products and departments. This experiment utilizes the assessment dataset described in Section 3.1 and the data of IT products described in Section 3.4. First, the assessment data was scaled and centered using standard scaling and PCA is applied for dimensionality reduction. Finally the data was clustered using K-means and the clusters were examined to find patterns in adoption as well as to identify areas of improvement for the different clusters.

This process utilized all of the 160 fully assessed products and all their individual self-assessment values for each of the adopted methods (81 in total). First step was to check PCA applicability for the experiment using correlation matrix (Figure 7) and scree-plot (Figure 8) of the Principal Components' explained variance.

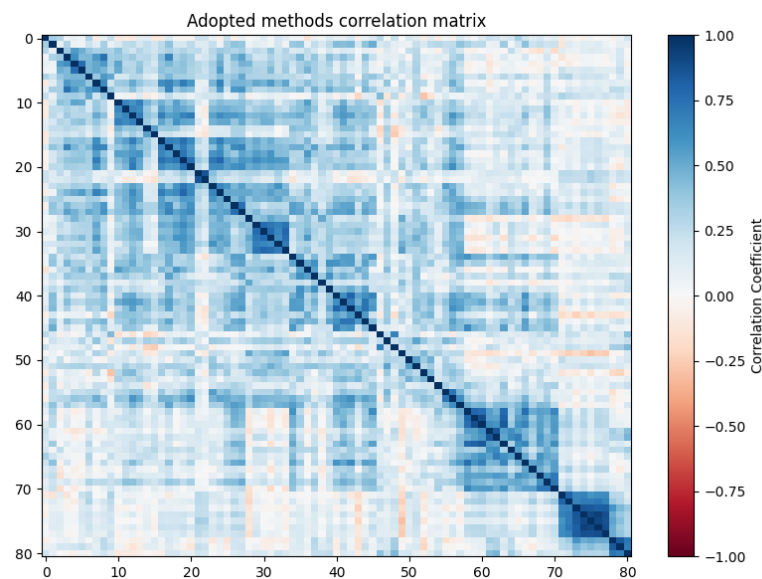


Figure 7. Correlation matrix of the entire Assessment dataset.

There is only moderate correlation between the variables, which suggests poor dimensionality reduction capabilities when using PCA. Although there is correlation between some of the adopted methods, these are mostly contained to the first half of the methods. Therefore, it is likely that PCA is unable to reduce dimensionality significantly.

The same is also visible from the scree-plot, where the total explained variance for the first two PCs is below 40%. This suggests that dimensionality reduction using PCA still requires usage of multiple dimensions.

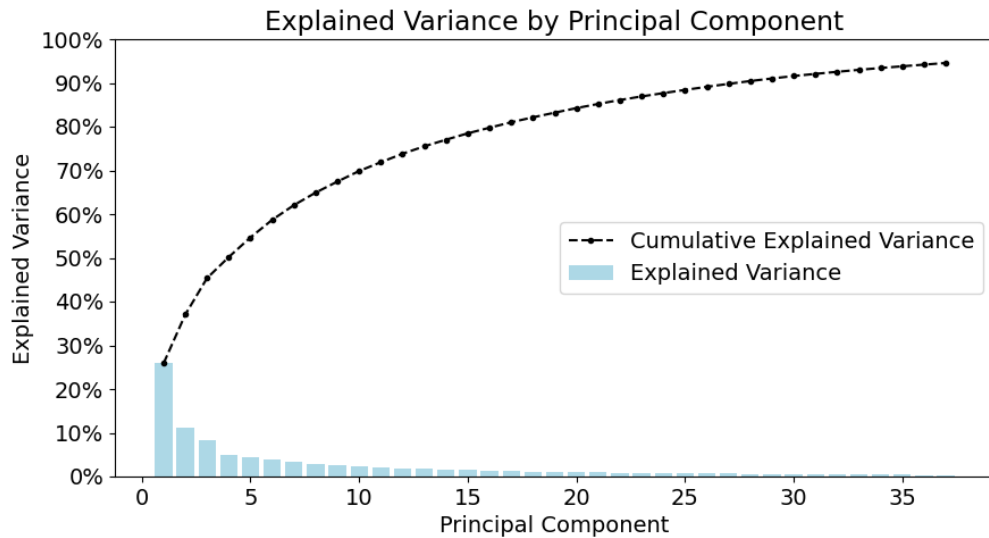


Figure 8. Scree-plot of the explained variance for each principal component (PC). The number of required PCs for explaining 95% variance was 37. The highest explained variance from PC1 was only 27%.

The resulting feature space contains 37 dimensions down from the original 81. The assessed products can be plotted in two-dimensional feature space using the first two PCs. This result is shown in Figure 9.

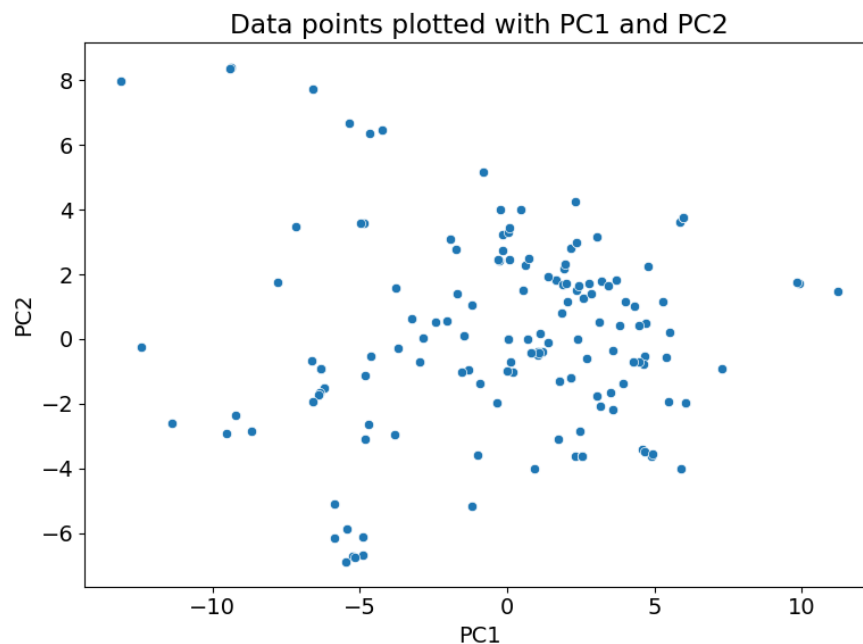


Figure 9. Dimensionality reduction using PCA. Each data point represents a single IT product. There are some smaller clusters of data points resembling smaller product groups. However, there are no clear large clusters at least based on the first two PCs. This means that silhouette values are likely to be lower than optimal for any number of clusters.

After dimensionality reduction, the data was clustered using the K-means algorithm. Decision for the optimal number of clusters was done by inspecting the silhouette scores for different numbers of clusters. The silhouette scores are displayed in Figure 10.

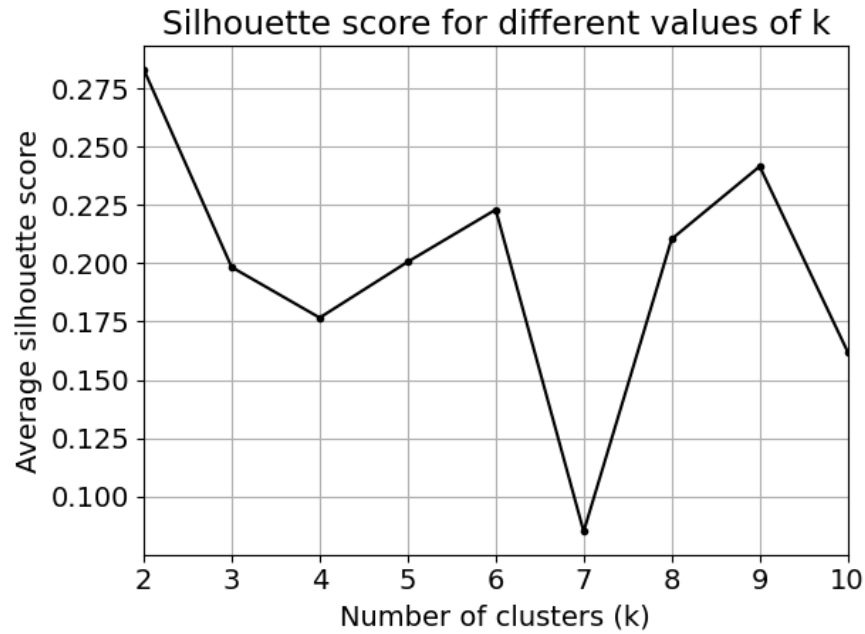


Figure 10. Optimal number of clusters selection based on silhouette scores. The best silhouette score (0.286) was achieved with just two clusters. There is not large difference in choosing any number of clusters since the silhouette values are lower than 0.3 for all numbers of clusters.

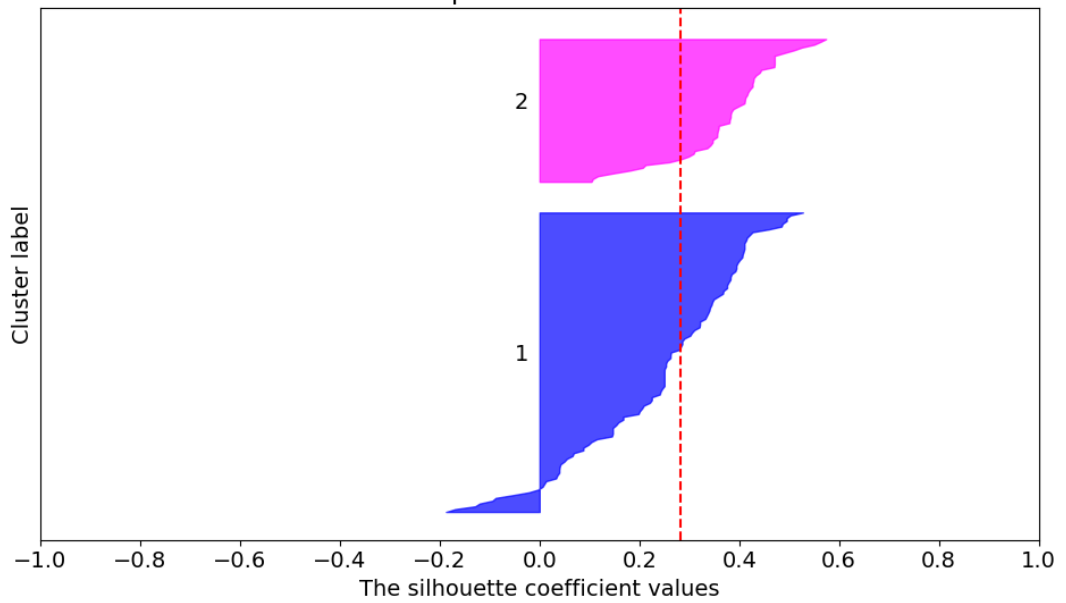
Based on the calculated silhouette scores, the optimal number of clusters appears to be two. Because of this the number of clusters to be used for K-means algorithm was set as two. It should be noted that as the low silhouette scores indicate poor cluster separation.

Next, K-means algorithm was applied to the data. The generated clusters are displayed in Figure 11, which shows both the silhouette scores for each cluster and the visualization of the clusters plotted in the first two PCs. Then, clusters were inspected using a heatmap to see how the adoption of method differs in each cluster. This heatmap is shown in Figure 12. The methods in this figure are represented by their short names and IDs. Refer to Appendices 1 and 2 to see detailed explanation of the methods.

In the heatmap it can be seen that Cluster 1 contains the most mature products in terms of adoption. Cluster 2 has the lowest maturity scores in almost all areas of adoption but it has products that have completed trainings and have defined their teams for the most part. The summarized statistics for each cluster are shown in Table 5.

Silhouette analysis for KMeans clustering on sample data with n_clusters = 2

The silhouette plot for the various clusters.



The visualization of the clustered data.

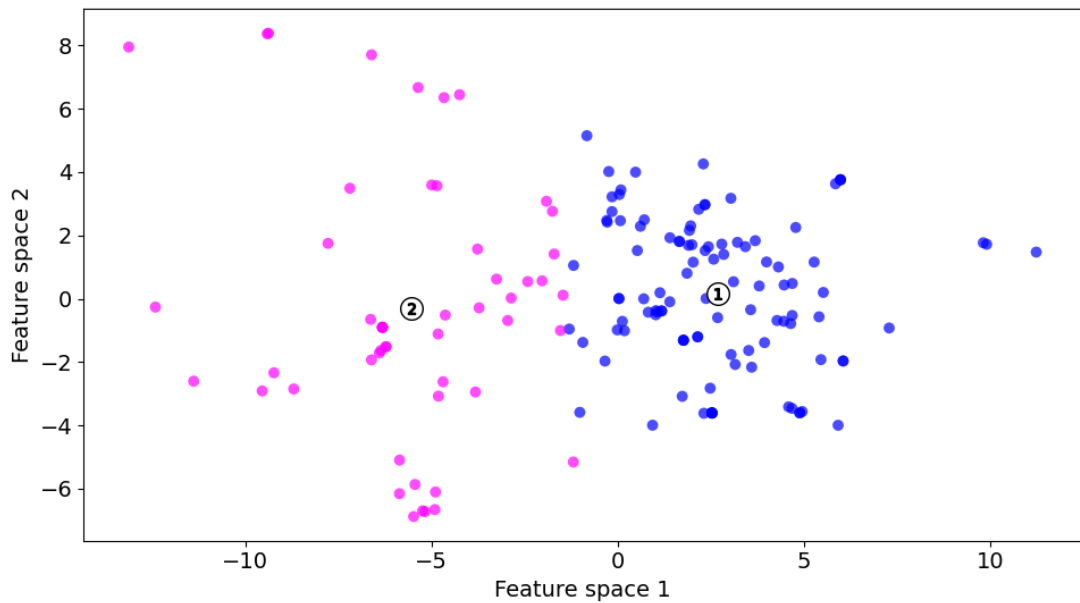


Figure 11. K-means clustering results visualized. The silhouette coefficient values for the data points belonging in the clusters are low, ranging from around 0.5 to -0.2. Also, the IT products have not been well separated visually.

Clusters were also inspected by looking at how the five different departments are represented by the clusters. Products labeled by cluster and the department they belong are plotted in Figure 13. Summary of how many products from each departments are in each cluster is shown in Table 6

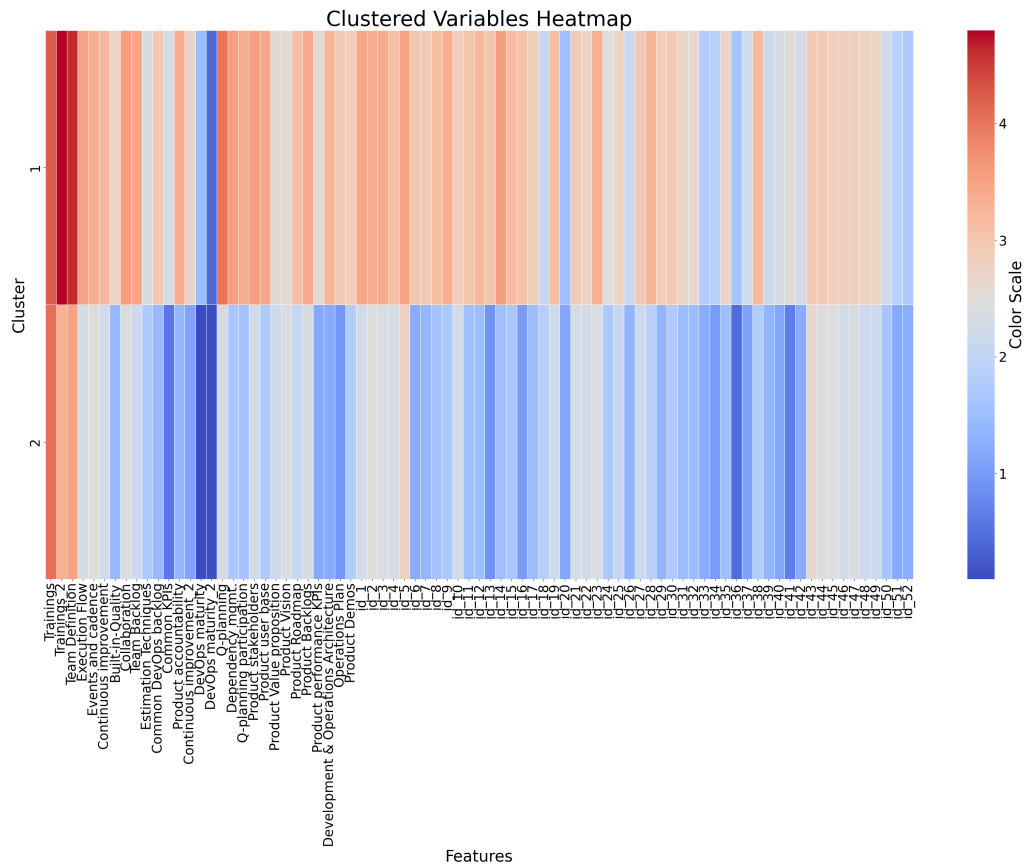


Figure 12. Clusters and their respective variable values represented in a heatmap. Cluster 2 has lower adoption values for all the methods while Cluster 1 has a higher adoption rate for almost all the methods. DevOps maturity for both clusters is low.

Table 5. Statistics for each cluster. Homegrown, SaaS/PaaS and COTS resemble the amounts of different types of applications found inside the IT products of the clusters. Count corresponds to the total amount of applications in all the products of a cluster. The average is the average amount of these applications in all products of the cluster.

| Metric | Cluster 1 | Cluster 2 |
|--------------------------|------------------------|------------------------|
| Average maturity | 3.19 | 2.60 |
| Ways of working maturity | 3.10 | 2.58 |
| Process maturity | 3.35 | 2.61 |
| Product age | 1.77 | 1.41 |
| Homegrown | Count 26, Average 0.24 | Count 10, Average 0.19 |
| SaaS/PaaS | Count 15, Average 0.14 | Count 1, Average 0.019 |
| COTS | Count 87, Average 0.81 | Count 52, Average 1.00 |

The distribution of departments in the clusters is mostly even for Departments 2 and 4. Departments 1, 3 and 5 are mostly represented by cluster 1. Based on the clustering analysis it is evident, that there is no major difference in the adoption profiles of different departments as they are not separated in different clusters. Age and type of product does

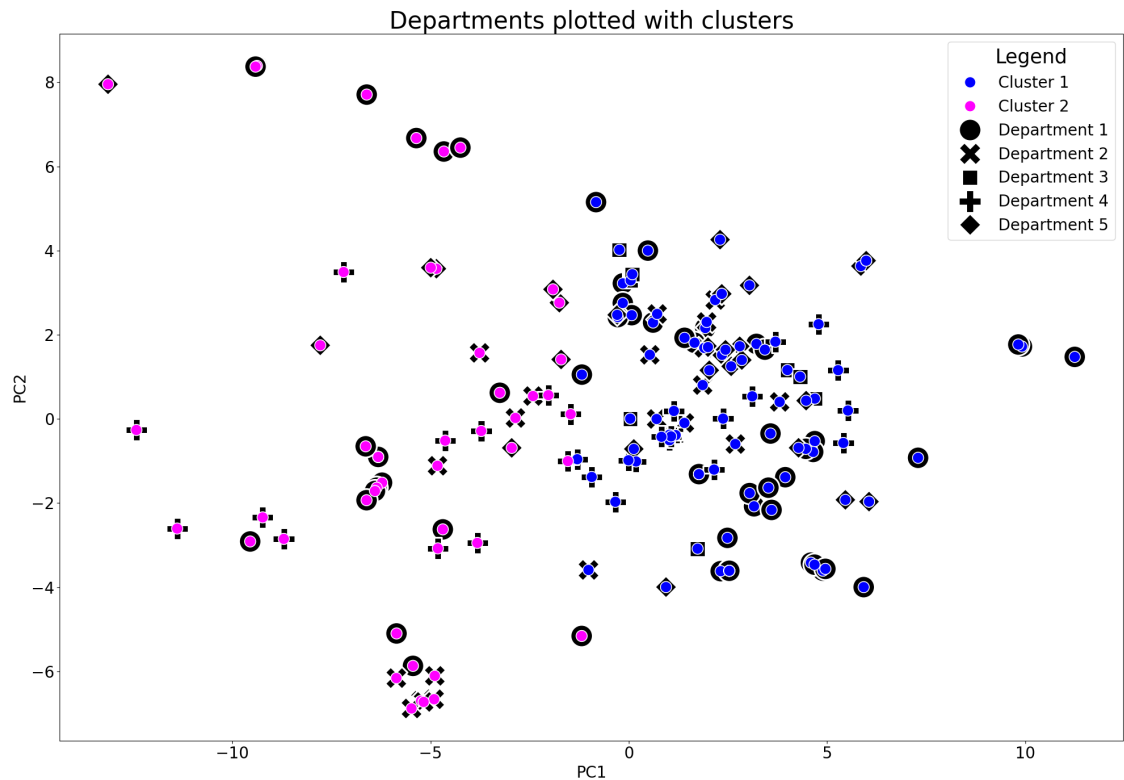


Figure 13. All IT products marked by cluster and department they belong in.

Table 6. Counts of IT products by department in each cluster.

| IT product department | Cluster 1 | Cluster 2 |
|-----------------------|-----------|-----------|
| Department 1 | 44 | 22 |
| Department 2 | 11 | 10 |
| Department 3 | 12 | - |
| Department 4 | 18 | 12 |
| Department 5 | 23 | 8 |

not appear to affect the adoption maturity significantly as the values are relatively close to each other. Adoption process within the departments has been inconsistent, signifying that either the products are significantly different and therefore utilize different methods or that they are doing their adoption unguided.

5.2.2 Analysis of adoption impact to working efficiency

The adoption of individual methods and their effects in respect to working efficiency was examined using PCA and correlation analysis. This study was done using the assessment dataset described in Section 3.1 and its correlation with working efficiency utilizing the

IT backlog management tool dataset described in Section 3.2.

For this experiment, the assessment dataset was modified by calculating the process-related methods together based on which operating area they belonged in. Data of working speed and work task completions were then merged with the assessment data for those products that were applicable. This resulted in a simple dataset, which contained assessment values for products (explanatory variables) and their corresponding work data (response variables).

PCA was then applied to this dataset to figure out the relationships and dependencies in the different adopted methods as well as their correlation to the work efficiency meters. The resulting number of principal components (PCs) and their explained variance is displayed in Figure 14.

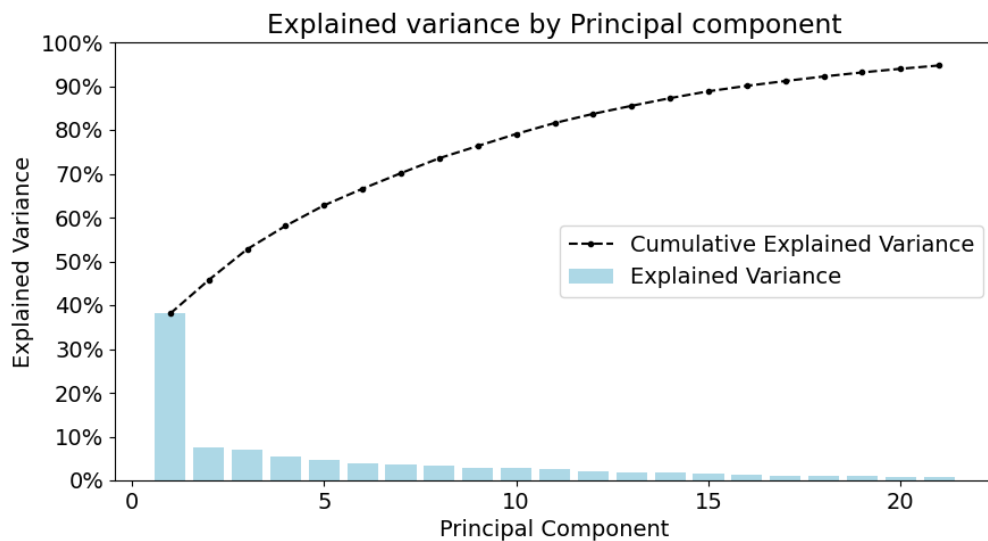


Figure 14. Cumulative explained variance based on the number of principal components (PC) as well as the explained variance of each individual PC. Together the first 21 PCs explain over 95% of the variance. The first two PCs explain a total of 46% of the total variance.

The loadings values for each of the methods and response variables are displayed in Figure 15. As can be seen from Figure 14, variance of the dataset is now better portrayed by the first principal components than in the previous experiment. This is because of the pre-made dimensionality reduction by merging some of the assessed methods together.

The plot of the loading vectors for the first two PCs (Figure 15) shows that most of the adopted methods correlate with PC1 while fewer correlate with PC2. The lowest correlation is with the last two variables, which do not have much correlation with the second

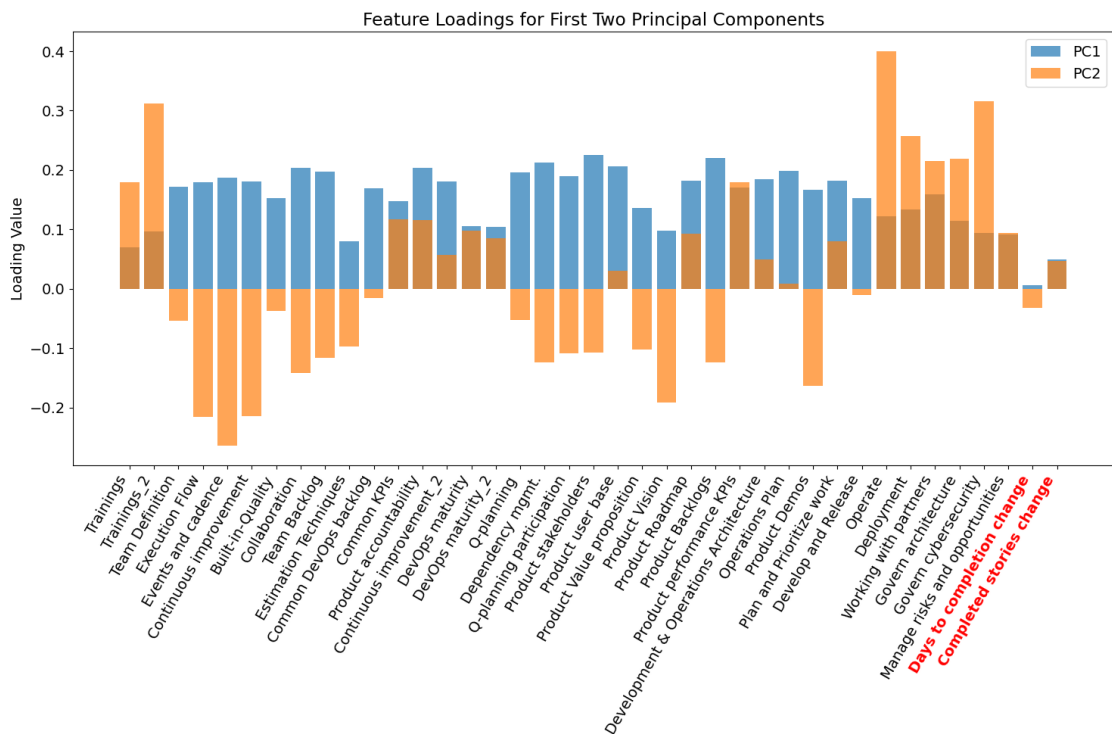


Figure 15. Loadings of the first two principal components. The response variables are presented in **red**. Based on the loading values, there does not appear to be much correlation for the adopted methods and changes in neither amount or speed of completed stories

principal component. The adopted methods do appear to correlate slightly with each other as well as PC1. There does not appear to be any correlation between the individual methods and the working efficiency meters.

The next step was to examine the correlation between the total assessment average and the working efficiency meters. The resulting correlation matrix with correlation values is displayed in Figure 16. Based on the correlation values, completion of tasks and working speed do not correlate much with having a higher maturity level in the new adopted ways of working. The information gained from correlation analysis matches with the information gained from PCA.

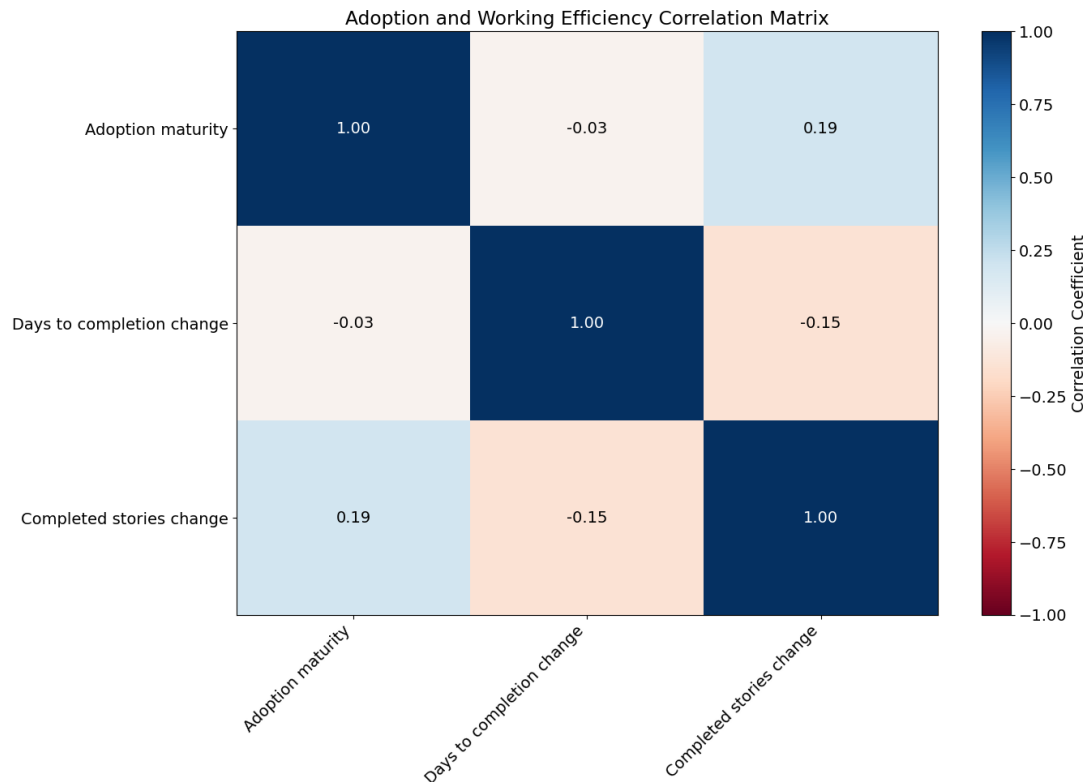


Figure 16. Correlation matrix of the adoption maturity and working efficiency meters. The correlation between all variables is low ranging from -0.15 to 0.19. Adoption maturity level has slight positive correlation with the amount of completed stories but no correlation with task completion speed. Completion speed and amount of stories also have low correlation together.

5.2.3 Analysis of employee satisfaction to adoption

The adoption of individual methods and their effects in respect to adoption and working satisfaction was examined using PCA and correlation analysis. This study was done using the assessment dataset described in Section 3.1 and its correlation with feedback data described in Section 3.3.

For this experiment the assessment dataset was modified by calculating process-related methods together based on which operating area they belonged in. Then product assessment values were grouped by product group by calculating their average adoption maturity level. Numerical variables of the adoption feedback data (adoption usefulness, satisfaction, employee satisfaction) were then merged with the assessment data for those product groups that were applicable. This resulted in a simple dataset, which contained assessment values for product groups (explanatory variables) and their corresponding feedback values (response variables).

PCA was then applied to this dataset to figure out the relationships and dependencies in the different adopted methods as well as their correlation to the feedback meters. The resulting number of principal components (PCs) and their explained variance is displayed below in Figure 17. The loadings values for each of the methods and response variables are displayed in Figure 18. As can be seen from Figure 17, variance of the dataset is now better portrayed by the first principal components than in the previous experiment. This is because of the pre-made dimensionality reduction by merging some of the assessed methods together.

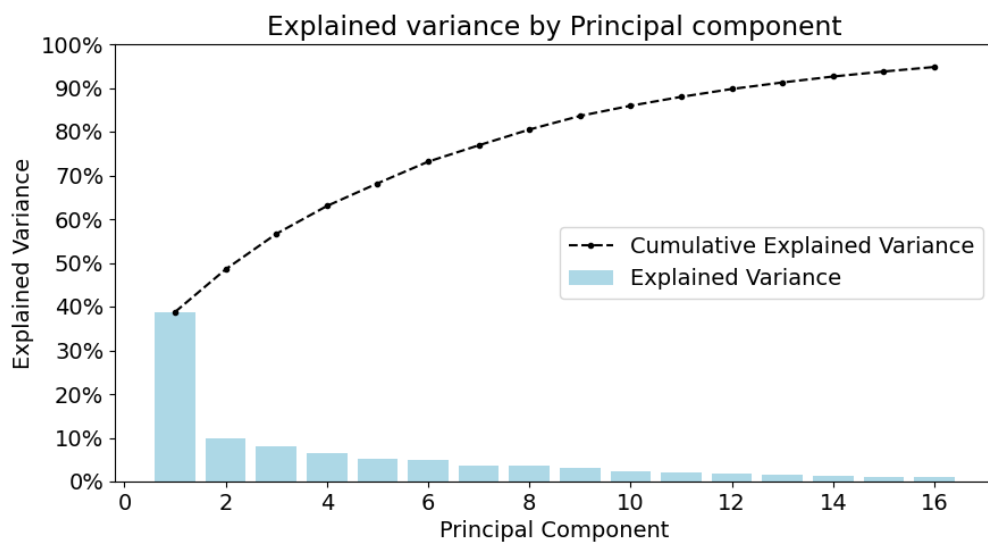


Figure 17. Cumulative explained variance based on the number of principal components (PC) as well as the explained variance of each individual PC. Together the first 16 PCs explain over 95% of the variance. The first two PCs explain a total of 50% of the total variance.

The plot of the loading vectors for the first two PCs (Figure 15) shows that most of the adopted methods correlate positively with PC1 while fewer correlate with PC2. Most noticeable positive correlation for PC2 comes from methods related to DevOps ways of working. Product management-related methods as well as adoption feedback variables slightly correlate negatively with PC2. Therefore, the adoption feedback values have slight positive correlation with product management related methods and reasonable negative correlation with DevOps ways of working.

The next step was to examine the correlation between the total assessment average and the feedback variables. The resulting correlation matrix with correlation values is displayed in Figure 19. Based on the correlation values, higher maturity level in the adopted ways of working does not correlate with how useful employees saw the adoption nor how satisfied they were in the process or their own job positions.

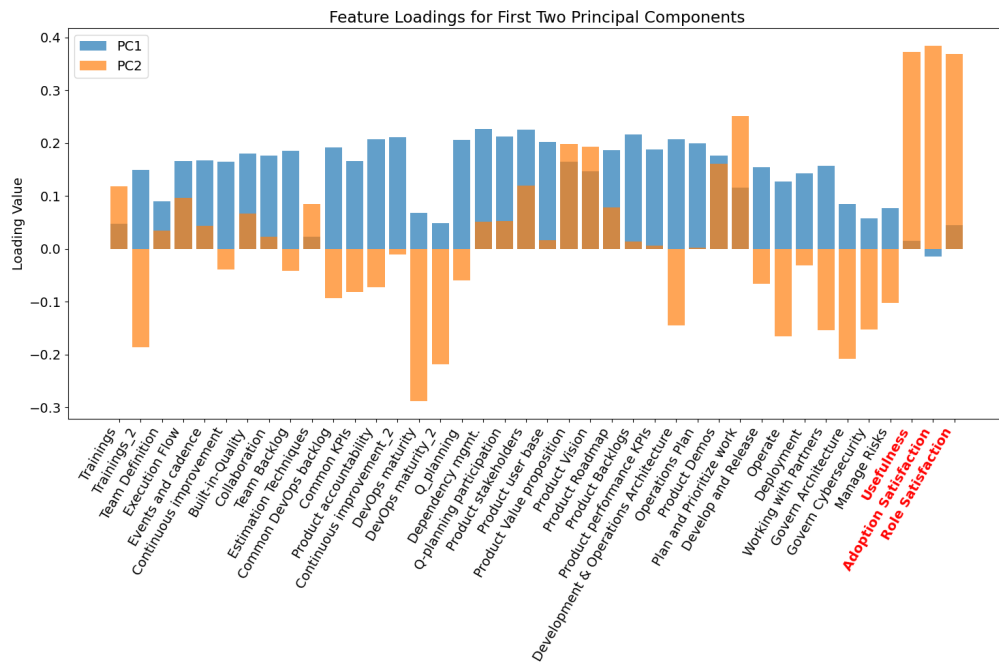


Figure 18. Loadings of the first two principal components. The response variables are presented in red. Based on these loading values the feedback variables have negative correlation with DevOps-related methods and slight positive correlation with product management-related methods.

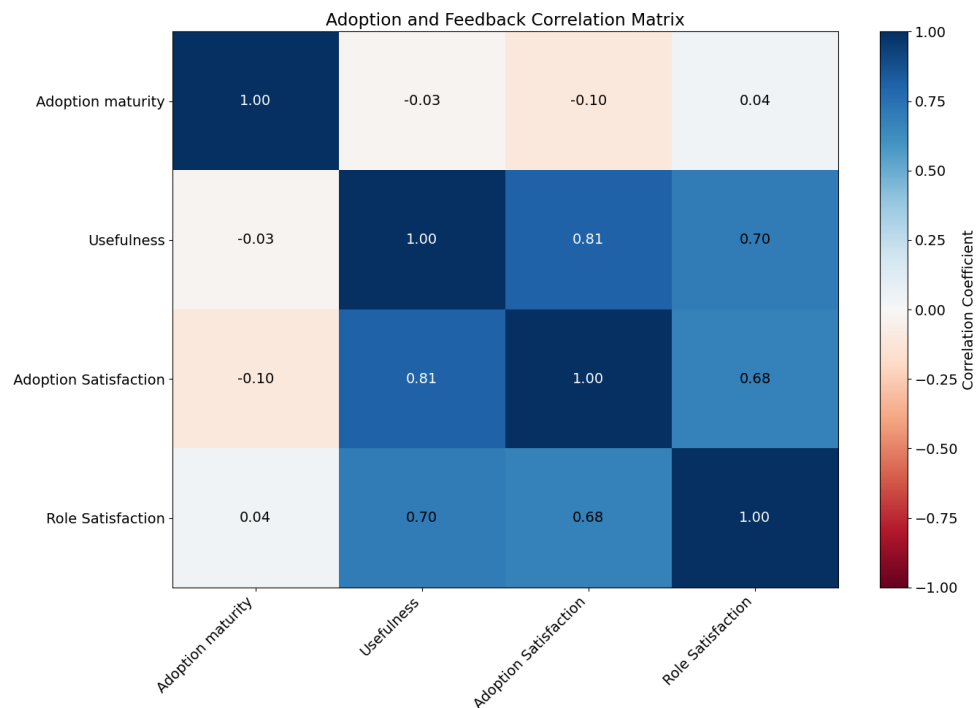


Figure 19. Correlation matrix of adoption maturity and feedback measures. All feedback variables have correlation values ranging from 0.68 to 0.81 with each other indicating that they have medium to strong correlation. Overall adoption maturity does not correlate with any of the feedback variables with highest absolute correlation value being negative -0.10 with adoption satisfaction.

5.2.4 Feedback analysis

Feedback dataset (described in Section 3.3) was further analyzed using visualizations of the dataset as well as reading the verbal feedback of the improvement suggestions. The summaries of answers are shown in Figures 20 and 21.

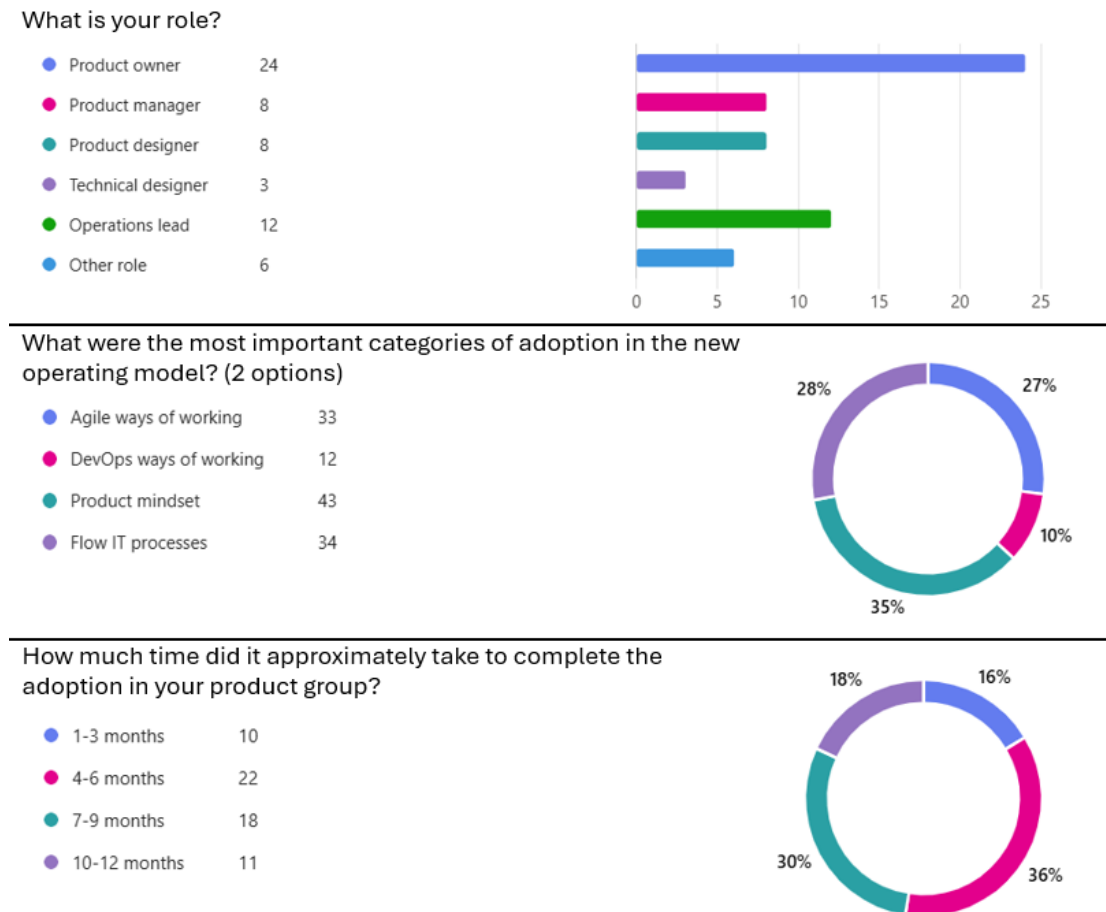


Figure 20. Summary of feedback questions. From the importance category it can be seen that DevOps ways of working were not considered to be as useful by the employees.

Looking at the feedback answer summary in Figure 20, there is a noticeable difference in how useful employees considered the different operating model categories. DevOps ways of working were not very highly rated while all the other three categories had gained more votes. Adoption time seems to have varied also quite a bit between the different product groups. The majority ($\approx 66\%$) of the product groups claimed to have completed the adoption in around 4–9 months.

The numerical feedback questions summary in Figure 21 shows that the overall satisfaction for usefulness of adopted methods, adoption process and role are similar being ap-



Figure 21. Summary of numerical feedback questions. The numerical values are similarly distributed in all of the questions. For the role satisfaction question there is a small split within the answers as there are no ratings of 5.

proximately 7.5 out of possible 10. The numeric feedback is also visualized in Figure 22 using department level aggregation.

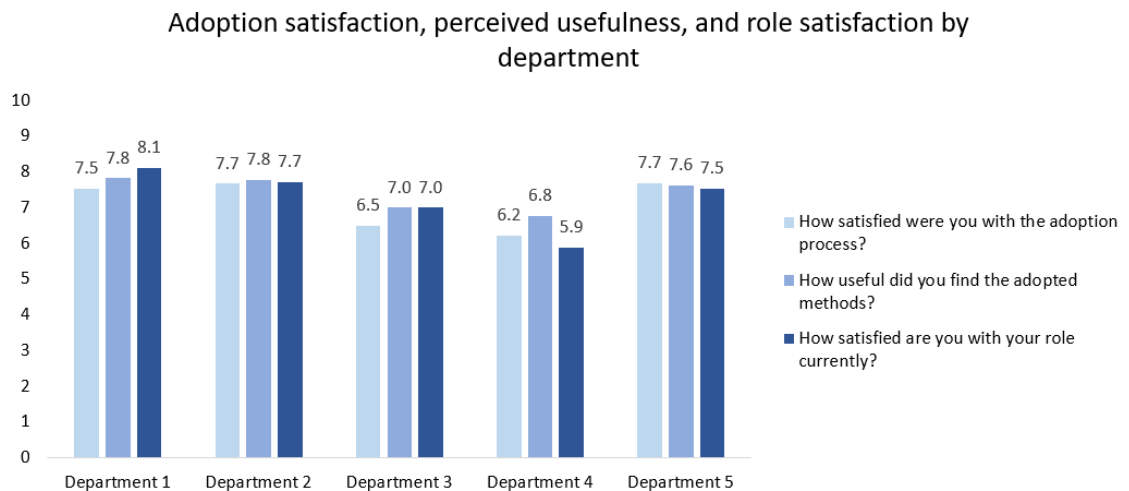


Figure 22. Adoption process satisfaction, perceived usefulness and employee role satisfaction by department. From the graph it is evident that Department 4 has lower values for all the three categories.

As seen in Figure 22, there is variance in the reported satisfaction values. Noticeably, Department 4 had the lowest survey scores out of any other department. The verbal feedback suggestions were also inspected using a Venn diagram to see how people gave improvement suggestions. The diagram is presented in Figure 23. From the diagram, it can be seen that the people who gave improvement suggestions for adoption process also were more prone to give improvements for methods. 52% of people did not give any suggestions.

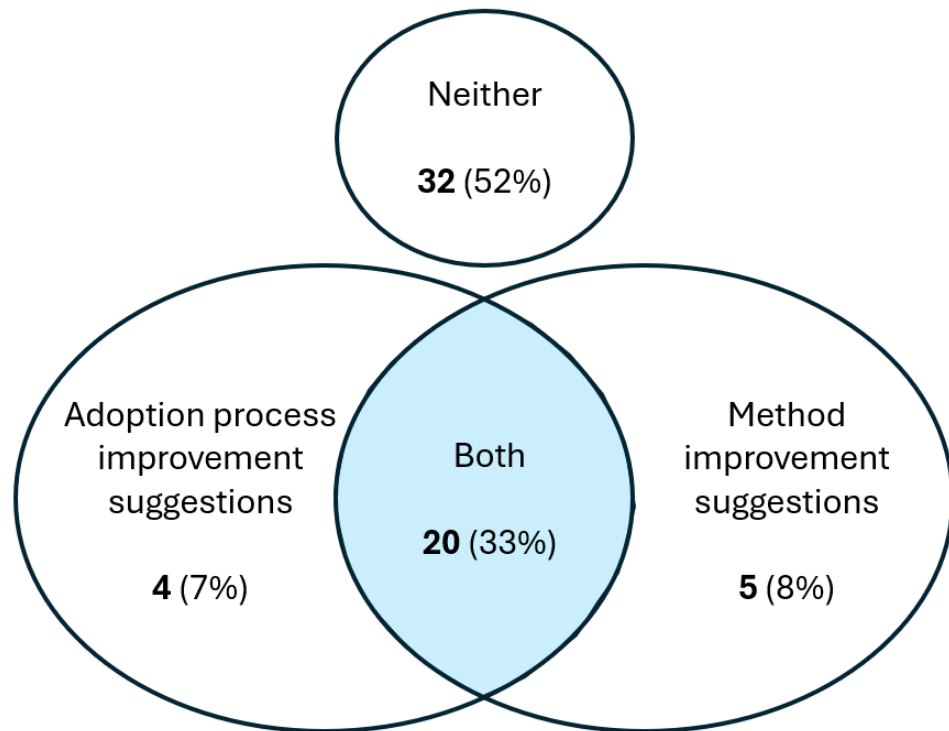


Figure 23. Venn diagram of given improvement suggestion amounts.

The dependencies between given feedback variables can also be portrayed by a correlation matrix in Figure 24. Adoption duration, which is a categorical value, was turned into a numeric value ranging between 1-4. Method and adoption process improvement suggestions were also turned into numeric values (1 for suggestion, 0 for no suggestion) to include them in the correlation analysis.

From the correlation matrix it can be seen, that satisfaction with methods, adoption process and role correlate together. As was evident from the Venn-diagram in Figure 23, improvement suggestions for adoption process and methods are correlated together. Also noticeable is that there is slight negative correlation between giving improvement suggestions and adoption satisfaction.

Verbal feedback suggestions were also inspected by reading them. There were not too many of them (29 total) so summarizing techniques were not necessary to use. Primary suggestions (and the amount) for adoption process were:

1. Simplify adoption process by simplifying and streamlining content (4).
2. Aim for clearer communication and better role definitions (5).
3. Give more time for adoption and increase training (6).

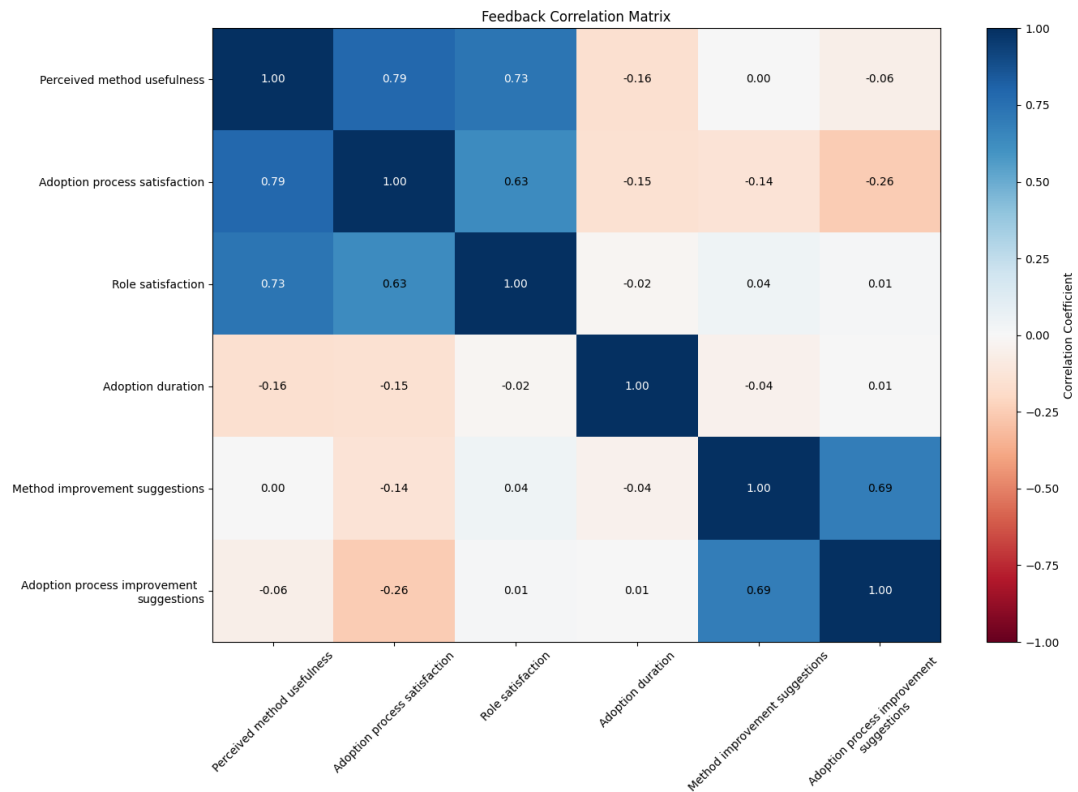


Figure 24. Correlation matrix of additional feedback statistics. Perception of method usefulness, adoption process satisfaction and satisfaction to current role are highly correlated with each other. However, these only have low correlation with adoption duration and whether people gave comments.

Suggestions to improve methods:

1. Focus on value creation for the organization should be improved as well as practical usage of methods (4).
2. Simplify and clarify content and methods (4).
3. Product mindset methods should be improved (5).
4. Clearer instructions and improve communication (5).

On average people were more satisfied with the methods than the adoption process. Communication and clarification were the biggest pain points for most people. Product mindset methods should be more focused on in the future.

6 DISCUSSION

6.1 Current results

Based on the results it appears that the initial goals of adopting the new operating model were not met. There is no clear evidence that adoption of the new ways of working and product management processes increased working efficiency or satisfaction. If this would be the case, adoption maturity should correlate with the response variables, namely survey satisfaction meters and working efficiency meters. In simpler terms; achieving higher maturity in method adoption does not impact working experience of employees positively or negatively. Possible reasons for this can be found from all of the separate analyses.

Clustering showed that the assessment dataset was not well separable to distinct clusters. This is because even though there are most definitely groups of similar types of products in the mix, these products did not necessarily have a similar adoption pattern. This could be due to the independent nature of the adoption process, meaning IT product owners adopted methods using their own judgment. This, however, could result in the methods not being optimal for their products. Overall, the adoption process does not appear to have been unified between the products as in that case there would most likely be more clear clusters, where larger groups of products had focused on improving maturity in similar areas.

Looking at the clusters' data, Cluster 2 was evidently the weakest in terms of adoption, as it had lower adoption values than any of the other groups. The age and type of application in the IT products did not appear to affect the adoption process that much, as the types were mixed in the clusters evenly. One noticeable feature from the heatmap of the clusters was that DevOps maturity was low for all groups, meaning most IT products were unable to implement these methods into their working. The same observation can be seen from the loading plots of PC2, where DevOps methods are mostly negatively correlated with satisfaction meters from given feedback. Therefore, it is possible to conclude that DevOps methods were not seen as useful or as easily adoptable into work.

The best information on why the adoption process was not very successful can be found from the verbal feedback given by the IT product workers. The numeric scores given in the adoption feedback are slightly low, averaging around 7.5, which would be only 75% satisfaction. Reasons for this seem to be that the methods were not seen as fully relevant to the specific IT product, too complicated or too theoretical. The change process was also

not fully properly communicated. There could have been a smaller amount of adopted methods than 81. All departments and IT product owners were required to assess all of the 81 methods for each IT product even if they didn't utilize them, which most likely resulted in confusion among the employees.

Some considerations should still be taken into account when analyzing these conclusions. First of all none of the datasets are completely reliable as they are measurements given by individual people under different circumstances. IT backlog management data relies on people knowing how to best use the tool for issue and work tracking. Utilization of the tool is still new to some employees so the best practices in monitoring work tasks is not perfected yet. This means the data might not be fully reliable. Feedback given by people is not fully reliable either, as getting a full picture of people's opinions would require a significant number of responses. In this case the response amount was only 61, which is only around 20% of the people that the survey was sent to.

The assessment dataset is also potentially biased as people might be more or less critical in their assessments in case of some products resulting in lower or higher assessment values depending on the case. Because the goal of KONE IT was to reach a maturity of over 3 during the adoption process, this was achieved but it raises the possibility that many of these assessments were evaluated higher than they should have been for the sake of reaching that goal.

6.2 Future work

During the work it was noticed that it was not easy to find comparable work data for all IT products. Therefore, there is a need for evaluation of the working data monitoring and data quality. There may also be a need for better evaluation metric for performance. The number of completed tasks as well as task completion speed do not necessarily tell the whole story of work efficiency, since some tasks take longer to complete than other by default. Hence, correlation to adopted methods may not be visible. Also, some tasks may not be added to the backlog management tool by the users, meaning not all the data is available for the analysis. This might mean that the tool users need to document their work better in order to use the software to its maximum potential.

Another result impacting factor may be the time frame of the study. Since adoption process of the new operating model began just a year ago, the effects may not be seen just yet. A new analysis should be done later, perhaps one year from now, to see if the results

have changed. In addition to the methods used in this study it could be useful to try out other research methods such as altering the clustering method from K-means to a density based method.

6.3 Improvement suggestions

There is evidence that the new working methods require some rework. Each method could be targeted to a specific group of IT products instead of including it in the adoption scope for all. This would allow the communication of these methods to be more on point for the specific IT product. Methods could also be adopted in smaller batches so that not all are introduced at once. For example only selecting five most important methods for the first year and making sure that they are properly taken in before moving on to the next set. It might be a good idea also to have a smaller control group instead of the whole KONE IT to test the methods and iron out the adoption process. After this the transition process with all departments might be easier.

One adoption manager per department was probably not enough either as each department hosted a number of different IT products which each required a very different adoption process. It might have been too difficult for one person to fully coordinate the process leading to the evidenced undesired results. The base idea of utilizing the methods from agile, DevOps and product management is good based on all previous studies. Just the process of trying to adopt all of them together was not that effective.

The simplification of the adoption process would also help with communicating the changes and help people see the benefits of the methods faster. This would likely show up as an improvement in the opinions of people in future feedback surveys. Time frame should also be taken into consideration. Some results may not show up yet as the adoption process was just completed, so the situation should be re-assessed after a year or two.

7 CONCLUSION

The objective of this project was to study the effects of adopting the new IT operating model in KONE IT. More specifically, the study focused on the effects of adopting methodologies that affected IT product management. This part of the new operating model contained tenets, methods and tools from different work optimization fields such as agile, DevOps and product management. This adoption was done over the years 2023 and 2024 and the progress was monitored via a self-assessment form for each of the different IT products in KONE IT.

The study was completed as a data analysis using the self-assessment form data as the base data set, which contained the information of the achieved adoption maturity for each IT product. In addition, work monitoring data, product data and feedback data of the adoption process was used to examine relationships between adoption maturity and its effects. From the data, it was explored how the adoption process was conducted inside the different IT products and departments of KONE IT using clustering. Correlation between the achieved adoption maturity and employee satisfaction and working efficiency was explored using correlation analysis and PCA. The feedback of the adoption process was also examined closer to get an evaluation of how the entire process was experienced by the people working around IT product management.

The results showed that although the target adoption maturity was reached, there was no observable correlation between achieved adoption maturity and working speed or working satisfaction, meaning adoption of methods did not show as improvements for the employees. The improvement points from the employees via the feedback survey showed that simplification and better communication of the process would be necessary as it was difficult to take in all the new information. Also the adoption process itself was designed to be similar for all IT products, even though they would have required unique guidelines as many of the methods were not applicable or hard to adopt for some of the products.

As the results showed that the adoption process had flaws, it is suggested that the process is simplified by focusing on the most relevant methods that impact work in a practical way. This would also help with the fact that there was only one adoption manager for each department. As there was a large mix of diversified IT products which would have required different adoption plans, amount of methods adopted per year should also be reduced. A control group could also be used to test changes before adopting them to the entire organization. Finally, these results should be evaluated again after a longer time period has passed as some effects of the adoption process might not be visible yet.

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Appendix 1. Adopted ways of working

| Category | Method short name | Method description |
|-----------------|---------------------------------------|---|
| Ways of working | Trainings | Team members participated in applicable Flow IT trainings. |
| | Trainings | Product Owner has completed Product Owner and Product Management Trainings |
| | Team Definition | Agile Team is clearly defined, its scope and Purpose have been updated in last six months |
| | Execution Flow | Team Executes work in 2 or 4 Week Sprints or Kanban with WIP limits |
| | Events and cadence | Team follows the agile ceremonies as agreed in the team (Sprint planning, Dailies, Demos, Retros) all team members participate and contribute in agile practices and ceremonies |
| | Continuous improvement | Team actively collect the input (retros and demo's) and feedback to continually improve its operations. |
| | Built-in-Quality | Definition of Ready (DoR) and Definition of Done (DoD) criteria have been defined for epics and stories and are being followed. |
| | Collaboration | Team has working practices to regularly align with other teams they're dependent on or they've interfaces with. |
| | Team Backlog | Team has single backlog in Jira which is regularly refined and all team members including partner employees plan their work based on it. Product owner own the backlog and accountable that it's up-to-date. All work for the team is planned to the one team backlog. |
| | Estimation Techniques | Epics and stories are estimated using story points |
| | Common DevOps backlog | Dev and Ops members use common backlog and plan together (e.g. Q-planning and/or Sprint /Kanban planning) |
| | Common KPIs | Dev & Ops members have common KPIs and targets to measure performance and success . We support each other to achieve the same. |
| | Product accountability | Product owner takes overall accountability for product outcomes including Dev & Ops. Works closely with Dev and Ops roles to achieve product roadmaps and operations performance targets |
| | Continuous improvement | Dev and Ops members together plan continuous improvement actions based on observed data, to enhance the functionality and experience of using the products |
| | DevOps maturity | The Dev & Ops members have together set the target maturity level (1/2/3) for each of the technical DevOps capabilities based on KONE IT DevOps capability framework and established a quarterly plan to reach the target maturity. |
| | DevOps maturity | The team has reached the target maturity level set for technical DevOps Capabilities for all the products in their scope. (Yes / No) |
| | Q-planning | Team carries out quarterly planning together with key stakeholders as per commonly agreed practices. Quarterly plans are communicated to all identified stakeholders and execution team members before start of the quarter. |
| | Dependency mgmt. | The team manages dependencies actively during Q-planning (Pre-planning weeks and planning days). Team follows the KONE IT and KTI time lines & practices for dependency management. |
| | Q-planning participation | All team members including externals and partner company representatives (Where applicable) participate in Q-planning and make planning commitments together with the team |
| | Product stakeholders | Key decision makers (funding and prioritization) and stakeholders (e.g. Business Process owners, Program leads) for the product are known. They participate in planning the product or delegated the responsibility to IT PO. (Planning here includes Roadmapping & Q-planning) |
| | Product user base | The target user base and their geographical locations for the product are known and agreed with the stakeholders. Team engages with the members of the user base (e.g. Key users) to understand their needs and validate the improvements. |
| | Product Value proposition | Product value proposition For the stakeholders and target users is defined and communicated to all relevant people |
| | Product Vision | Product vision exists for next 2 -3 year horizon |
| | Product Roadmap | The product in scope of the team has a roadmap that has been updated in the last 3 months and aligned with stakeholders. Product Roadmap is communicated to all key stakeholders including those in the Areas. (Roadmap should cover new major features, continuous development themes, operations related activities) |
| | Product Backlogs | Product backlog exists. Team prioritizes their work in-line with the product roadmap and time critical issues that need team attention |
| | Product performance KPIs | A set of product performance KPIs, agreed with the stakeholders and decision makers, are regularly measured and corrective actions planned when needed. |
| | Development & Operations Architecture | Products in scope have identified the development and operations architecture. This includes critical technical elements and other products (e.g. IT platforms) and IT services that are needed for delivering promised experience to end users in production environments. (Consider, full operations architecture, including IT Platforms, Cloud Infrastructure, access control systems etc. Consider integrations to local IT systems and services. Note that some platforms may offer platform as a service and handle infra issues by themselves) |
| | Operations Plan | Operations plan for the product exists and takes into account the required Technical elements, products & platforms, IT services (e.g. AskIT) target users and Performance commitments (e.g. SLAs). This plan is reviewed at least once a quarter and improved based on the learnings during the quarter. Product operations are as per this plan. |
| | Product Demos | Product demos are held with key users and stakeholders during the development, at least once a quarter for the purpose of feedback. (If there is no active development this is not applicable). |

Appendix 2. Adopted working processes

| Category | Method category short name | Method description | Identifier |
|--|---|---|------------|
| Working Processes | Plan and Prioritize Work | Product owner gathers the demands from global business and functions, Areas and Frontlines. | ID_1 |
| | | Product owner and the agile team identify technical and operational needs to remove technical debt, improve quality or security of a product. | ID_2 |
| | | Product owner and the agile team analyze the needs, identify dependencies and estimate the capacity needed for developing them. | ID_3 |
| | | Product owner prepares the roadmap, sets quarterly priorities and manages dependencies together with the Product Manager. | ID_4 |
| | | Product Owner acts as the bridge between the Agile Team, business and stakeholders. | ID_5 |
| | Develop and Release | The product designer documents the IT product design that complies with architecture and security guidelines. | ID_6 |
| | | The agile team defines the IT product test approach and test automation targets. | ID_7 |
| | | The agile team decides the quality steps and ensures that they are followed for each increment. E.g. Peer reviewed designs, unit tested code, Regression testing. | ID_8 |
| | | The agile team ensures the operational readiness before each release. | ID_9 |
| | | The agile team gathers early and frequent feedback from key users. | ID_10 |
| | The agile team agrees on release governance actions and applies them to all releases. | ID_11 | |
| | Operate | Adherence to ITSM Processes: Agile team must strictly adhere to the ITSM processes that are defined by the KONE. | ID_12 |
| | | Participation in Planning and Retrospectives: Ops lead are required to actively participate in Quarterly and Sprint planning sessions as well as retrospectives. | ID_13 |
| | | Incident and Service Request Logging Ops lead must ensure that every incident and service request has a ticket logged within KONE's ITSM tool. | ID_14 |
| | | Problem management: Agile team need to create RCAs for high impact incidents | ID_15 |
| | | Change Management: Changes identified by Agile team, as part of the development, are recorded by them in Jira and reflected in the release calendar. Changes recorded by Ops lead must also be reflected in the release calendar. | ID_16 |
| | Deploy business Changes and Realize Benefits | Configuration Item (CI) Lifecycle Management: Agile team should periodically review the entire lifecycle of a Configuration Item and updated in the Configuration Management Database (CMDB). | ID_17 |
| | | Deployment of business changes follows KONE Way change management principles. | ID_18 |
| | | Every IT Product must have clear change management steps for continuous development. | ID_19 |
| | | Project manager does rollout planning according to KW methodology if change is implemented through project. | ID_20 |
| | | Product owner agrees roles and responsibilities between IT and business in global / area. | ID_21 |
| | | Product designer analyzes the change impact against the size and complexity of the change before starting development | ID_22 |
| | | Agile team deploys every change according to agreed approach (e.g. quarterly release and key user calls) | ID_23 |
| | | Product designer prepares training plan and end user educational materials as needed | ID_24 |
| | | Ops Lead prepares the team to support users technically during and right after the change | ID_25 |
| | | Product owner follows the benefit realization against the leading and lagging indicators and KPIs together with business owner | ID_26 |
| | Working with Partners | Understand partner's contractual obligations and deliverables, ensure they are adopted by the agile team where applicable | ID_27 |
| | | Agree how partners are working as part of the agile team, while making sure contractual obligations are fulfilled | ID_28 |
| | | Follow up partners' performance based on the contractual agreement and agreed ways-of-working in the agile team | ID_29 |
| | Govern Architecture | Document the current architecture | ID_30 |
| | | - IT Product | ID_31 |
| | | - E2E technical value stream | ID_32 |
| | | Define the reference architecture | ID_33 |
| | | Define the target architecture, long term & short term | ID_34 |
| | | Perform technology evaluations | ID_35 |
| | | Describe the architectural roadmap from current state to target state | ID_36 |
| | Maintain the architecture documentation | ID_37 | |
| | Govern Cybersecurity | Conduct EA Health Checks | ID_38 |
| | | Ensure that the relevant architecture reviews and approvals are timely performed and collected | ID_39 |
| | | KONE baseline security requirements must be implemented for all IT products regardless of their security impact level. | ID_40 |
| | | IT Products with major security impact must be onboarded into IriusRisk for threat modelling and security requirements identification. | ID_41 |
| | | Security impact must be reassessed if the IT product has significant design changes. | ID_42 |
| | Manage Risks and Opportunities | Each product must be security tested and critical/high vulnerabilities must be fixed prior to the production release. | ID_43 |
| | | Security risks must be assessed. Residual risks must be accepted by product owner before the release and the decision must be documented | ID_44 |
| | | Identify Risks and Opportunities | ID_45 |
| | | Identify and execute mitigation actions to keep risk level under control | ID_46 |
| | | Assign owners for identified risks and opportunities | ID_47 |
| | | Assess and Prioritize Risks and Opportunities | ID_48 |
| | | Plan mitigation actions and assign to the correct action owner | ID_49 |
| | | Execute mitigation actions and re-assess likelihood and impact | ID_50 |
| | | Continuously review and update Risks and Opportunities | ID_51 |
| | | Escalate on need basis to the correct governance forum | ID_52 |
| Update Risks and Opportunities for Quarterly Review | | | |
| Report Program/Project Risks and Opportunities in Program/Project Steering | | | |