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# THE INFLUENCE OF TEAM-TECHNOLOGY SATISFACTION ON THE QUALITY OF HUMAN-GENERATED DATA

*'A CASE STUDY AT ROYAL VOPAK'*

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BY

J.J.J KERSTEN

STUDENTNUMBER: 4082044

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## **Graduation committee**

Chairperson : Dr. R.M. Verburg, *Section Economics of Technology and Innovation*  
First Supervisor : Dr. L. Rook, *Section Economics of Technology and Innovation*  
Second Supervisor : Dr. Ir. G.A. de Reuver, *Section Information and Communication Technology*  
External Supervisor : Dr. L. Brand, *Chief Information Officer (CIO) at Royal Vopak*

## ABSTRACT

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In the light of the fourth industrial revolution, referred to as Industry 4.0, big data is becoming the key resource of modern companies. In order to safely harvest the potential benefits of the Industry 4.0, a high level of data quality is essential. Yet, modern companies experience poor data quality levels, mainly in human generated datasets. To improve human generated data quality, the IT usage behaviour should be studied. This research investigated the influence of team-technology acceptance and satisfaction on human generated data quality. The research was conducted at Royal Vopak and studied the data from the Decision Support System: INFOR. The study followed a multimethod comparative field study design, in which interviews combined with a literature review provided input and practical validation for a survey and a data quality assessment. The Structural Equation Modelling (SEM) regression was conducted to investigate the relation between TAM variables and data quality of the Decision Support System (DSS). Results confirmed that the perceptions of riskiness, ambiguity had effect on data quality levels. Also, evidence for the influence of perceived usefulness and perceived ease-of-use on overall satisfaction was found. Future research should use these results in developing training and development programs to improve team-technology interaction and data quality levels.

*Keywords: Big data, Industry 4.0, Team-Technology interaction, TAM, Data Quality, Decision Support Systems*

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## PREFACE

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This research is one of the fruits of my labour at the Delft University of Technology. Over the past years, I was taught in the fields of Mechanical Engineering and Management of Technology. Both of which helped me to perform an internship at Royal Vopak as part of my master studies graduation project. Working at Vopak I gained practical experience with the complexities of organisational change. I assume it does not require explanation that understanding the business processes of a stock-listed firm like Vopak in a short period of time, is a hell of a job. Therefore, it is no exaggeration to state that I am proud of the learning curve I experienced and the results that were obtained. In the last six months, I learned to translate a business problem into a research problem and to develop a research methodology to come up with a solution. In this process I experienced multiple setbacks, which I managed to endure and to stay motivated. Especially, the mitigation between science and business requirements proved to be a complex endeavour. Nevertheless, it is in my belief that the results from this research are practically and scientifically valuable. Although, this thesis is the result of my hard work, I could not have done it without all the support and help I received.

I am very grateful to all the people from Vopak that made me feel welcomed at their firm and supported me in my research. In particular, I would like to thank Leo Brand for giving me the opportunity to perform my graduation internship at Vopak. His enthusiasm and connections enabled me to keep on going and exploring the world of Vopak. I also dearly appreciate all the time and effort Karin Drinkwaard, Wouter Boerefijn and Rob Heutinck have given me. They helped me to understand the maintenance process and the role of INFOR in it. Without them it would have been a thousand times harder to find my way through the process and INFOR program. Next to the people from Vopak, I want to express my gratitude to my first supervisor from the TU Delft. Professor Laurens Rook helped me a great deal in structuring the research process and in understanding the principles of scientific research. His belief and interest in my topic motivated me to push the limits of my research and to explore new theories, concepts and methods. Last but not least I would like to thank my friends, fellow students and of course my parents and sister for their moral support.

I hope you will enjoy reading this thesis.

Delft, September 2017

Joris Kersten

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## EXECUTIVE SUMMARY

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### BACKGROUND

In the era of the fourth industrial revolution, which revolves around the advanced digitalisation of IT systems in industrial industries, data is becoming one of the most valuable and critical resources. Competitive advantages that can be achieved by adopting new IT innovations, depend heavily on the quality of data retrieved from operational processes. Yet, in their continuous race for competitive advantage, modern companies underappreciate the importance of data quality. In traditional industrial organisations, operational data is often of poor quality. This leads to unnecessary costs, unsafe situations and flawed decision-making. The best example of the consequences of poor data quality is the case of NASA's *Challenger* space shuttle. The *Challenger* space shuttle was launched in 1986. Almost immediately after the launch the space shuttle exploded and all astronauts died. Investigation revealed that the accident was caused by failures in a particular mechanical part, called O-rings, due to non-resistance of temperature drops. The research commission found out that, although the problem of the malfunctioning O-rings was already known, the launch was not postponed. Therefore, the commission concluded that flawed decision-making was the main cause of the accident. Many arguments for the flawed decision making were given, but one that got much attention was the poor data quality of their decision support systems (DSS). The information about certain mechanical parts provided by the DSS was based upon inaccurate, incomplete and inconsistent data. Many believe the poor data quality fed to data analytic programs, led to wrong decision-making and ultimately to the death of the *Challenger* astronauts.

### PROBLEM

Illustrated by the *Challenger* incident, the consequences of poor data quality and thus the reasons to avoid them are clear. Industrial data is usually provided in two ways: by machines or by humans. Especially with the human as data generator, maintaining a high data quality standard proves to be a difficult endeavour. In contrast to machines, humans are unique in their perception of using and motivation to use a technology. Moreover, humans are prone to be influenced in their usage behaviour by other humans, which causes potential bad usage behaviour to spread throughout organisations. The behavioural influence humans exert on each other is even larger in business context. Modern organisations have adopted a team-approach to solve complex business problems. Teams are characterized by high task dependency, cohesiveness and common goal and mind-set. Therefore, employees within teams are especially vulnerable to copy bad usage behaviour from their peers. In other words, poor data quality in organisations is a socio-technical problem that should be avoided and solved to ensure a high level of safety in harvesting the potential benefits of the fourth industrial revolution.

### OBJECTIVE

To understand the socio-technical causes of poor data quality, this thesis turns to various psychological variables explaining technology acceptance and satisfaction. Literature into the field of technology acceptance models (TAM) and satisfaction provides us with variables that explain the human perception of a technology their satisfaction while using it. Usually IT usage behaviour is measured through self-reporting scales and consists of frequency of usage and objective of usage. However, current study hypothesizes that usage behaviour also consists of a quality of usage part, next to the frequency of usage and objective of

usage. It is in this belief, that this thesis set out to investigate the influence of the technology satisfaction level of teams on the quality of the human-generated data.

## PROCESS

The research was done in a multimethod comparative field study design at Royal Vopak. Vopak is the world's largest independent petrochemical storage company. With 39 terminals across 5 different continents, Vopak is a global multinational, that is stock-listed in the Netherlands. In their operations Vopak uses several Decision Support Systems. The DSS analysed in current study was the INFOR program, which is the enterprise asset management system Vopak uses to support the maintenance process. Data from INFOR gives information about asset failure, maintenance performance and cost allocation. However, currently, INFOR is mainly used for day-to-day tracking and monitoring of incidents and maintenance progress. The multimethod approach for investigating the team-technology satisfaction of INFOR existed of three phases: first, exploratory interviews with managers from the IT and the Operations departments are conducted. The interviews validated the theorized variables of technology satisfaction and they provided deeper understanding of INFOR and delivered a proxy for the data quality assessment. The second phase consisted of a survey and a data quality assessment of INFOR. The survey and data quality assessment were conducted at 23 terminals that had at least three years of experience with INFOR. The survey consisted of four technology acceptance variables and one overall satisfaction variable:

- **Perceived Usefulness (PU):** PU measures the degree to which a person believes that using the technology would enhance his or her job performance.
- **Perceived Ease-of-Use (PEoU):** PEoU measures the degree to which a person believes that using a particular system would be free of effort.
- **Perceived Unambiguity (PA):** PA measures a person's perception of vagueness of the probabilities of the outcomes of a technology's prospects due to lacking information.
- **Perceived Riskiness (PR):** PR measures a person's anticipatory appraisal of his or her vulnerability to a loss by accepting a certain prospect, in this case the prospects of a certain technology usage.
- **Overall Satisfaction (SF):** SF measures the overall experience in terms of satisfaction.

The survey was distributed to all INFOR accountholders from the 23 selected terminals. The accountholders per terminal functioned as an operational team and thus the individual survey results were aggregated to team-level. A data analysis of the INFOR data was conducted by measuring the data consistency of a proxy. The proxy measurement was assumed to represent the current level of data quality of INFOR as a whole. In the third phase, the results from the survey, aggregated to team-level, and DSS data quality assessment were analysed by conducting Structural Equation Modelling (SEM).

## FINDINGS AND CONCLUSIONS

The SEM regression resulted in several findings. First, it was found that TAM variables, when enriched with the perceived riskiness and perceived unambiguity variables, are usable in the analysis of mandatory team-technology collaboration. TAM had never been applied at team-level, and therefore this result has a large scientific contribution in the field of Information Systems research, in which TAM is a frequently used tool. Second, the variables of Perceived Usefulness and Perceived Ease-of-Use were found to be powerful predictors of Overall Satisfaction. Moreover, it was found that Perceived Usefulness has moderating effect

on Overall Satisfaction, which is consistent with prior research. Third, a significant negative influence of perceived riskiness on data consistency of the proxy was found. This indicates that the more risk the members in a team perceive, the lower the quality of the data they generate will be. Fourth, a significant positive effect of perceived unambiguity was found. This signals that when team member perceive that they lack the information to correctly use INFOR, the data consistency will be lower. The perception of lacking information, i.e. unambiguity, does not mean that teams do not have sufficient information to use the system, but they only perceive it. In other words, they experience uncertainty as they do not have the confidence that they have enough information, regardless of the actual level of knowledge they have. Fifth, no significant relation was found between the level of Overall Satisfaction and data Consistency of the proxy, and even more interestingly the effect measured was negative, indicating increased data consistency when satisfaction levels are low. This is interesting as it was not consistent with prior research. Explanations for the unexpected effect and its non-significance lie in the limitations of this research.

## LIMITATIONS

Naturally this study has some limitations and (corresponding) recommendations for further research. First of all, although the sample size at individual-level (N=143) is adequate, at team-level (N=23) the sample size is rather small. This causes the results of this research to be slightly underpowered. Although studies of small sample sizes are unavoidable when the total population is small, they are not preferable. Additional statistical techniques should be applied in future reproductions of this thesis to account for the loss in statistical power due to small sample sizes at team-level. Second, the data quality assessment has been performed by analysing a proxy on its consistency. It has been assumed that the data consistency of the proxy is representable for the data quality of the whole program. However, this might not be the case. Therefore, further research should be focused on analysing the data on more quality dimensions than only consistency of INFOR as a whole. Third, culture and demographics were not incorporated as control variables. However, respondents reported limited understanding of the questions in the survey, which might be caused by language differences. Furthermore, it is possible that, although the sampled terminals have three years of experience with INFOR, accountholders of those terminals have not. This would cause differences in their response and therefore it is recommended that future reproductions of this research measure the control variable of years of experience.

## RECOMMENDATIONS FOR FUTURE RESEARCH

A practical recommendation of this research is the development of training modules based upon the results of this research. With the global overview of the level of data consistency per terminal, and the survey responses of the team members, tailor-made training should be designed to improve the quality of data generation. In order to do so, additional research has to be performed on the topic of training design and implementation. A second practical recommendation is to perform in-depth interviews and observations at the terminals with high levels of data consistency. The goal here is to identify best practices in team-technology interaction and data generation, which can be replicated in other terminals.

In terms of recommendations for future scientific research, the limitations mentioned above already provided several next steps to be taken. This would result in a reproduction of current study in a longitudinal setting at a larger company, i.e. a company with the availability of more teams. By performing a longitudinal study, it becomes feasible to study more dimensions of data quality. A longitudinal study, also makes it possible to investigate the effect of an intervention, such as a training program, in a pre-test-post-test design.

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# 1 INTRODUCTION

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In the era of the fourth industrial revolution, which revolves around the advanced digitalisation of industrial industries and is often referred to as the Industry 4.0 (I4.0), data is becoming one of the most valuable resources (Bauer et al. 2015). Therefore, to gather the prospected benefits of this fourth industrial revolution, data needs to be collected continuously and of high quality. Yet, in traditional industrial organisations, operational data is often of poor quality (Haug et al. 2011). To understand the causes of poor data quality, Management of Information Systems (MIS) research turns to the different sources and generators of data (Hashem et al. 2015). It is in this belief, that this thesis sets out to investigate the human's behaviour regarding the generation of data and its effect on data quality.

## 1.1 BACKGROUND

The notion of data comes from the Latin word *Datum*, meaning 'a given'. Data, the plural form of *datum*, was first used in Roman philosophy, where it was defined as *a fact known from direct observation* (Dictionary.com n.d.). In modern society, data is mainly stored in spreadsheets, in computers and other digital applications. In the last decades, the computing power, and storage capacities of digital machines drastically increased the generation, processing and interpretation of data and enabled advanced analytics of data (Greenwood 1999). For instance, Google was one of the first to use data to actually predict a certain phenomenon. In 2008, they placed an article in *Nature* in which they explained a method to detect influenza epidemics using search engine query data. Google used search engine inputs related to health-seeking behaviour and related this to symptoms of the Influenza disease. By doing this on huge scale they could detect Influenza disease epidemics in a very early stage (Ginsberg et al. 2008). This is an early example of advanced analytics of big data to solve complex problems. In 2014, Hal R. Varian described the large scale usage of data to predict certain phenomena and used the notion of *Big Data* (Varian 2014). In his research, Varian argues that the evolution of *Big Data* made existing data manipulation tools and techniques inadequate. He examined several stages of data analytics (collection, processing and interpretation) and the most common manipulation techniques and tools that are used. His research resulted in a list of shortcomings of traditional data handling techniques and tools to facilitate manipulation of big data. Importantly, the most significant factor on his list, was the level of data quality. Low data quality hampers the reliability and integrity of data and therefore makes predictions uncertain.

Recently, in addition to Varian's scientific article, (big) data quality gained importance in business setting with the rise of Industry 4.0 (I4.0). The concept of I4.0 comprises a variety of IT innovations and macro-level developments that enable the emergence of a digital and automated industrial organisation as well as the digitisation of the supply- and the entire value chain (Kagerman & Johannes 2013). The concept of I4.0 was first mentioned at a convention in Germany as a proposal to launch a development direction for the German high-tech industry. Driven by IT innovations in sensor technology, wireless network performances and processor capabilities, the collection of big data became possible and affordable (Chen et al. 2016; Bello et al. 2016; Weichhart et al. 2016). Alongside the introduction of I4.0, advanced data analytic algorithms to detect (previously hidden) correlations between business processes and to provide input for I4.0 related concepts like Artificial Intelligence, Cloud Computing and Cyber Physical Systems, were developed (Lee et al. 2014; Borana 2016; Armbrust et al. 2010; Bagheri et al. 2015).

When big data is examined and meaningful correlations are found, data turns into information and the I4.0 benefits for businesses become clear. First, predictive powers of big data analytics based on

statistical models may forecast maintenance and prevent unexpected shutdowns. This enables reductions in operational costs and thus increase productivity (Lee et al. 2015). Secondly, new customer information improves tailored customer services and customized products. This will enable new business models that will stimulate growth of revenue (Kans & Ingwald 2016). Thirdly, advanced communication capabilities between humans and machines improve the transfer of knowledge, nowadays some call this Knowledge Management 4.0 (KM4.0) and it is expected to drive a large stream of future research (Gandolfo et al. 2016). It will sharpen learning curves and will drastically shorten R&D cycles (Gilchrist 2016). Lastly, I4.0 will help decision-makers by providing real-time information which enables them to take decisions based upon the most up-to-date data of their business processes (Kagerman & Johannes 2013).

Although the prospected benefits of I4.0 seem clear, they can only be achieved if advanced data analytics is possible. One of the biggest threats to successful data analytics is the *poor quality of data* (Green 2017). In that respect a famous example of the criticality of poor data quality can be found in the disaster with the NASA *Challenger* space shuttle, where inconsistencies and errors in the data gave the wrong information and led to fatal decisions (Fisher & Kingma 2001). The NASA *Challenger* space shuttle was launched in 1986. Almost immediately after the launch the space shuttle exploded and all astronauts died. Investigation revealed that the accident was caused by failures in a particular mechanical part, called O-rings, due to non-resistance of temperature drops. The research commission found out that, although this was already known, the launch was not postponed. Therefore, the commission cited flawed decision-making for allowing the launch in the first place. Many arguments for the flawed decision making were given, however, one that got much attention was the data quality of their decision support systems (DSS). The information about certain mechanical parts provided by the DSS was based upon inaccurate, incomplete and inconsistent data. Many believe the poor data quality fed to data analytic programs, led to wrong decision-making and ultimately to the death of the *Challenger* astronauts (Fisher & Kingma 2001).

The *Challenger* example illustrates that data analytics algorithms are designed to work within the limits of certain formats and protocols, and interpretations are as reliable as the data upon which it is based. But when data is collected from a variety of sources, its reliability might be hard to verify and thus the data is prone to be unfit for use. Therefore, generating and collecting high quality data are key challenges for the successful implementation of I4.0 (Hashem et al. 2015).

Data generation can basically be done either by machines or by humans, but especially human-generated data increases the chances for data quality issues (Lauvsnes & Korsvold 2015). Unlike machines, human individuals are unique and their activities differ in consistency, accuracy and thoroughness. This endangers the quality of their activities and thus the quality of the data they generate. With the addition of the human element, data generation in IT applications becomes a problem of socio-technical nature (Leonardi 2012; Lauvsnes & Korsvold 2015). In other words, to improve human generated data quality and harvest the prospected benefits of the I4.0, we must investigate the socio-technical interaction and collaboration between human and machine. Next paragraph will elaborate further on the issues of human-generated data and consequentially the objective of this research.

## 1.2 RESEARCH OBJECTIVE & QUESTION

In the case of the *Challenger* space shuttle disaster, the human generated data in the Decision Support System (DSS), which is an IT data visualisation program that aids managers in decision-making, contained serious quality problems (Fisher & Kingma 2001). The Rogers Commission, leading the incident investigation, identified three fatal flaws in human data generation as the cause for the disaster.



One of the theories offered to explain NASA's flawed data generation process emphasized group thinking and team pressure as key factors of data quality issues (Fisher & Kingma 2001). Others highlight the role of the human and its perception regarding the DSS as contributing factor (Fisher & Kingma 2001). Also in broader sense, research acknowledges the role of cognitive responses like beliefs and perceptions regarding IT as contributing factor to explain IT usage behaviour (Davis 1989; Venkatesh 2000; Al-Gahtani & King 1999). Nelson et al. (2005) associated perceived system quality, i.e. satisfaction, to information, or data, quality. They found significant correlations between the two variables, but measured the system satisfaction and data quality variables at the level of the individual and through self-reported scales.

Modern organisations embrace a team-approach to solve complex business problems and therefore it makes sense to review the correlation between the satisfaction with an IT-system and the human-generated data in that IT-system from a team perspective (He et al. 2017). Moreover, according to Straub et al. (1995) self-reported scales do not reflect actual data quality precisely and thus lack reliability that is required for high level decision-making. Therefore, it would be interesting to investigate the influence of team-technology acceptance on actual data quality levels in DSS.

In succession of the *Challenger* disaster, the objective of this research is to identify the influence of team-technology satisfaction on the quality of human generated data in Decision Support Systems. Therefore, this research will address the following main question:

***What is the influence of team-technology satisfaction on the quality of human generated data in Decision Support Systems?***

The results of this investigation may reveal antecedents of human generated data quality in team-technology interaction behaviour. These results can be used to focus data quality improvement efforts, through customized training and team development. Improved data quality reduces the risk of misinformed decision-making and may prevent disasters like the *Challenger* incident from happening in industrial organisations.

### 1.3 THESIS STRUCTURE

This thesis contributes to data quality research by examining the influence of team-technology satisfaction on data quality in Decision Support Systems. To do so, a literature review on data quality in Decision Support Systems, Technology Acceptance and Satisfaction Models and Team-Technology interaction will be conducted. Chapter Two ends with a conceptual framework and hypothesis. In Chapter Three, the three-phase research methodology is discussed. Chapter Four presents the procedure and results of exploratory interviews from the first phase. The pre-analysis of the survey and data quality assesment will be presented in Chapter Five, or the second phase. The third phase entails the regression analysis and testing of the hypothesis. The results will be handled in Chapter Six. Lastly, Chapter Seven will discuss all the results and limitations, elaborate on scientific and practical relevance and conclude the research by addressing directions for future research.

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## 2 LITERATURE REVIEW

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In this section, the most important theories and concepts to be used in the present research will be discussed. This will start with examining the topic of Data Quality in Decision Support Systems. Then, the topic of Technology Acceptance will be examined. Lastly, literature regarding teams and team performance will be summarized. This chapter will end with a conceptual model and hypothesis.

### 2.1 DATA QUALITY IN DECISION SUPPORT SYSTEMS

One of the major prospects of I4.0 is the benefit of faster (real-time) and better informed decision-making. Modern companies use Decision Support Systems (DSS) from brands like SAP, Oracle, Ultimo or INFOR, in order to facilitate this improved decision-making. However, as explained in the introduction, data quality is fundamental to achieve prospected benefits. This section first discusses Decision Support Systems in general and then examines Data Quality Management and Assessment.

#### 2.1.1 Decision Support Systems

Research in the field of Decision Support Systems (DSS) stems from the 90's. DSS is a subset of the larger group of Management Information Systems (MIS). Next to DSS, MIS contains Enterprise Resource Planning (ERP) systems, Customer Relations Management (CRM) systems, Supply-Chain Management (SCM) systems and Knowledge Management Systems (KMS) (Laudon & Laudon 2014). Opposed to other MIS, DSS is often used at lower hierarchical business levels. DSS facilitates heavily changing, unstructured decision-making. Scott Morton (1978) was the first to introduce the concept of using a computer to support semi-managerial decision-making (Arnott & Pervan 2005). DSS was later extended and combined with various streams of research. This led to different aspects of DSS research: Personal Decision Support Systems (PDSS), Group Support Systems (GSS), Executive Information Systems (EIS), Negotiation Support Systems (NSS) and Intelligent Decision Support Systems (IDSS) (Arnott & Pervan 2005). The different streams make DSS a broad field of research that is holistically defined by Daniel J. Power (2008):

*“Decision Support System is a general term for any computer application that enhances a person or group’s ability to make decisions (Power 2008, p. 149).”*

Normally, PDSS are small programs that are developed for the individual or one decision task. This follows the philosophy of supporting individual managers instead of the ‘whole organisation’ (Arnott & Pervan 2005). In juxtaposition with PDSS, GSS focusses on supporting decision-related meetings of a group or team. This might be in geographical proximity to one another, but it also entails virtual teams (Paul et al. 2005). EIS involve the data-driven DSS to facilitate reporting of an organizations activities in order to support executive management (Arnott & Pervan 2005; March & Hevner 2007). This term often is mentioned in combination with Business Intelligence (BI): patterns and knowledge discovered by applying algorithmic or statistical analysis to acquired data (Power 2008; March & Hevner 2007). NSS is mostly similar to GSS, but it entails computer-based programs that focus more on the negotiation part of decision-making (Arnott & Pervan 2005). Lastly, there is the most recent version of DSS: Intelligent Decision Support Systems. IDSS is based upon IT innovations like machine learning, data mining, neural networks and artificial intelligence. Essentially, IDSS aims at replacing organisational decision-making by managers by rule-based expert systems and neural networks ran by a computer (Yam et al. 2001).

Especially this last form of DSS, is on the rise in many industries. An Intelligent Decision Support System basically understands what data is meaningful for solving a particular problem or question. Business Intelligence and Analytics (BI&A) (1.0 to 3.0) revolves around analysing text, web and networks, by mining data, try linkages between them and interpreting the results (Chen et al. 2012). Although the rewards of such a system may be promising, its demands regarding data quality are extensive. Therefore, it is of interest how data quality is measured and what causes changes in data quality of human-generated data.

### 2.1.2 Data Quality

*Data* in itself is an old concept that often is used in close relation with *Information*. However, the two are very different. Fox discusses various definitions of the concept of data to define a comprehensive definition that follows linguistic and usefulness criteria (Fox 1994). He compares several definitions that review data as: a set of facts, measurements of observations, raw material of Information, symbols, a collection of triples  $\langle \epsilon, \alpha, \nu \rangle$  and, following from the last one, as a set of representable triples. Only this last one respects the criteria that he has set. This collection of triples, invented by Tsichritzis and Lochovsky (1982), is the widely accepted description of a data point. It is describing any data item as a collection on the basis of a value  $\nu$ , that is selected from the domain of the attribute  $\alpha$ , to represent the attribute's value for the entity  $\epsilon$ . This 'collection-of-triples definition' of *data*, however, fails to distinguish between the recording of data and representation of data, so Fox added them to obtain the following definition:

*Data is a collection of triples (value, attribute and entity) recorded from a real-world object or phenomenon and represented on a medium as a set of rules (Fox 1994).*

From this definition, it becomes clear that the record of the real-world object or phenomenon is subject to interpretation and therefore open for errors. The percentage of errors in a dataset determines the quality of this data. Already in 1980, Brodie defined data quality as:

*"a measure of the extend, to which a database [of collections of triples] accurately represents the essential properties of the intended application (Brodie 1980 p.246)."*

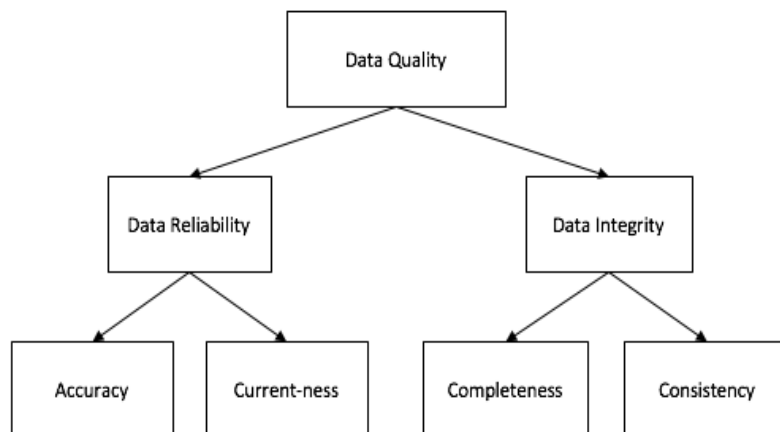


FIGURE 1: COMPONENTS OF DATA QUALITY

A database, mentioned in this definition, is the storage of data, i.e. collections of triples. The definition of quality of the data in such a database, is a combination of data reliability and integrity. Reliability is divided as the accuracy and current-ness dimensions of the data, whereas integrity consists of completeness and consistency dimensions (Figure 1).

As can be observed assessing and improving quality of data can be very rewarding, but it is also a very costly and timely endeavour. Total Data Quality Management (TDQM) is the most commonly used method for maintaining data quality. The TDQM cycle consists of continuously defining, measuring,

analysing and improving data (Wang 1998). Defining is done at high level, where functionalities for the data users are conceptualized, and at lower level where the basic data items and their relationships are identified. Also, the quality requirements, from the perspective of the different data users, have to be defined at this stage. Next, the data should be measured on the basis of the results of the first step. This means that specific measures are coupled to the four dimensions, accuracy and current-ness as part of reliability and completeness and consistency as subsequent of integrity (Wang 1998).

#### 2.1.2.1 Data Reliability

Reliability consists of two dimensions: accuracy and current-ness. *Accuracy* is defined as to what extent the values,  $v$ , describe the intended and actual value,  $v'$ . The *current-ness* of the data is reviewed as how far the data is out-of-date, or in other words: if data is recorded at time  $t$ , but analysis is done at time  $t+3$ , then the data is out-of-date and does not represent the real-world phenomena at the current time anymore. Assessing data reliability is very difficult. In terms of the accuracy, one has to review if the data is actually describing the real-world phenomenon or object accurately. This means manually tracing and tracking the real-world phenomenon or object and not merely checking the data items from behind the computer screen. Also, current-ness is difficult to assess, because one has to go back in time to verify whether the logged date matches the real date of observation. Although data reliability is difficult to assess, data integrity is far more easy to observe (Jayawardene et al. 2013; Batini & Scannapieco 2016; Redman 1998).

#### 2.1.2.2 Data Integrity

Integrity is divided in completeness and consistency. *Completeness* of data is the difference of the number of entries compared with the total number of asked entries. This might be observable in missing entire entries and thus observing blank spaces, but also in the form of duplications. Completeness is a data integrity issue and is better observable than reliability issues, as you don't have to go into the field, but one can use automated, detection algorithms or manual labour to analyse datasets. Next, there is the dimension of *consistency*, which is also a part of integrity. It refers to the fact that data items have to be logical in relation to each other. In the case of physical integrity, data obtained from physical equipment like sensors have to show a certain logic and linearity. When values deviate often and significantly this could signal a broken or wrongly placed sensor and the dataset is dirty. In the other case, semantic integrity requires a certain logic and consistency in recording and representing of data by non-physical entities. It is in this domain where human errors, such as the ones introduced earlier for the *Challenger* space shuttle example, often are cause of poor data quality and possibly to life threatening incidents (Fox 1994; Tejay et al. 1995; Maletic & Marcus 2000; Jayawardene et al. 2013).

#### 2.1.3 Conclusion

In this section, research about Decision Support Systems was summarized, and dimensions of data quality were identified. To understand quality of human-generated data, one must take into account the accuracy, current-ness, completeness and consistency of the data. Next paragraph will examine technology acceptance in the context of team-technology interaction.

## 2.2 TECHNOLOGY ACCEPTANCE AND SATISFACTION IN MANDATORY ENVIRONMENTS

To understand the antecedents of the quality of human generated data, this thesis uses the theory of Technology Acceptance and links this to team-technology interaction. This section examines Technology Acceptance and related Satisfaction Models and links this to mandatory environments.

### 2.2.1 Theory of Technology Acceptance Models

Technology Acceptance (TA) is one of the most widely used concepts to predict successful adoption of new IT technology. Research towards TA originates in social psychology. It revolves around the behavioural intention to use a new technology (Lauvsnes & Korsvold 2015; Davis 1989). In psychological research 'behavioural intention' was initially investigated and explained in the Theory of Reasoned Action (TRA) and the Theory of Planned Behaviour (TPB) (Ajzen 1991; Ajzen & Fishbein 1975). In a comparison study, Madden *et al.* (1992) described TRA as follows (Figure 2):

*"TRA states that behavioural intentions, which are the immediate antecedents to behaviour, are a function of salient information or beliefs about the likelihood that performing a particular behaviour will lead to a specific outcome (Madden et al. 1992 p.3)".*

Traditionally, TRA and TBP were developed to understand quitting behaviour of addicted individuals, for example in the desire to quit smoking. The concepts gave insight into the question to what extent addicts intended to quit smoking, the generalized variables that motivated them to quit smoking and their actual behaviour of quitting to smoke. Following the original intention of the models and the example of smoking addiction, TRA states that this behaviour is directly determined by one's behavioural intention to smoke, which is explained by an individual attitude towards smoking and a perception of subjective norms towards the behaviour of smoking. Therefore, it seems logical that when somebody has a positive attitude towards smoking and experiences positive subjective norms regarding smoking in general, it is very likely he will have the intention to start smoking, and thus he will. However, it can already feel there is missing some element of human control.

The TPB extends the TRA with an external factor of Perceived Behavioural Control (PBC). This means that users have a greater control over their behavioural control, and thus over their intended behaviour, when they possess more resources and opportunities related to the intended action (Madden *et al.* 1992). In the smoking example this would mean that although the individual has a positive attitude towards smoking and it perceives positive subjective norms regarding smoking in general, the individual still has the capacity to control his behaviour, or at least has the perception that it has the power to control his behaviour. For example, the individual feels it does not have enough money to buy cigarettes and therefore the behavioural intention does not result in actual behaviour.

In further research towards technology acceptance, these two models are often mentioned as foundations behind behavioural intention and they are combined and extended to fulfil specific means and target-groups.

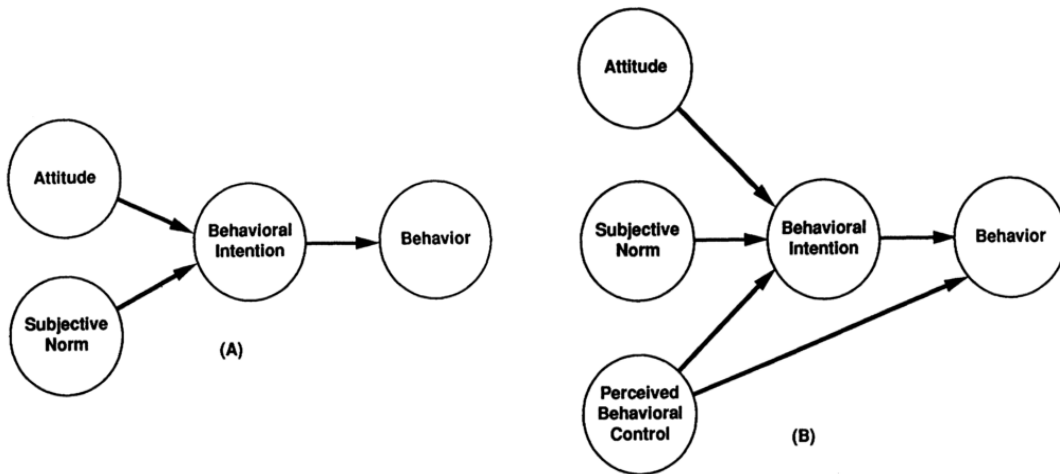


FIGURE 2: REPRESENTATIONS OF TRA (A) AND TPB (B) (MADDEN ET AL. 1992)

Davis (1989) was the first to combine TRA and TBP with the purpose to explain technology acceptance behaviour of electronics consumers. His research tested the hypothesis that predicted usage of new technology is explained by someone’s Perception of Ease-of-Use (PEoU) and Perceived Usefulness (PU). PEoU is defined as the degree to which a person perceives the use of a system ‘free-of-effort’. Davis claimed that, everything else held equal, a system that is perceived easier to use than another, is more likely to be adopted. PU is defined by deriving the word useful: capable of being used advantageously. In other words, PU refers to someone’s perception of the advantage he will gain by using something. These two independent variables influence the intention to use a technology that is a direct predictor for actual usage. The relation between these constructs (Figure 3) is the base for the first Technology Acceptance Model (TAM) that uses user perceptions regarding a certain technology to predict the usage adoption of that technology.

TAM theory is applied in various researches (Hwang et al. 2015; McFarland & Hamilton 2006; Lauvsnes & Korsvold 2010; Davis 1986). In later studies, additional antecedents to the TAM variables were identified. For instance, Venkatesh (2000) found Computer Self-Afficity, External Control, Anxiety and Playfulness to be prior factors of ease-of-use. Also, prior factors for PU were found along with some contextual factors. In the next paragraphs, the prior factors of PU will be elaborated on and some contextual factors of TAM in relation to technology satisfaction and mandatory environments will be explained.

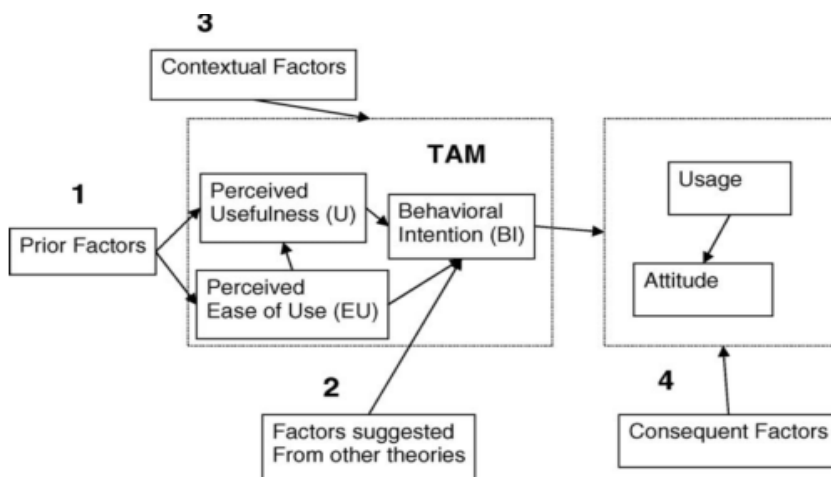


FIGURE 3: MODIFICATIONS ON THE ORIGINAL TAM DESIGN (KING & HE 2006)

## 2.2.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

One of the most popular extensions of the original TAM model is the Unified Theory of Acceptance and Use of Technology model (UTAUT). UTAUT combined elements of existing acceptance and behavioural intention

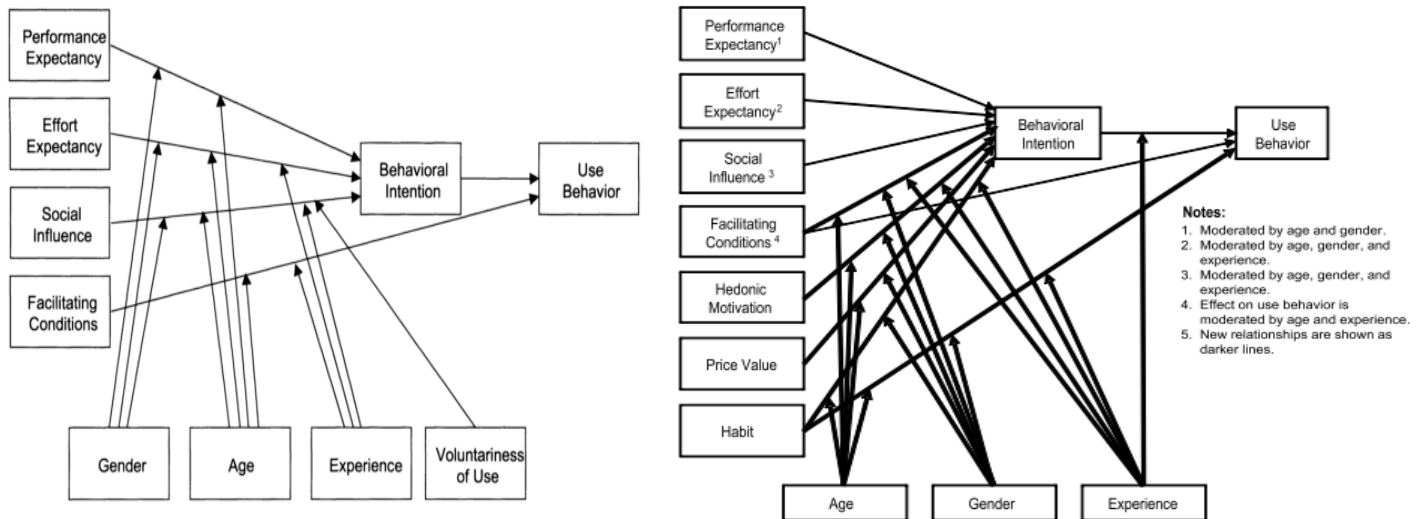


FIGURE 4: THE ORIGINAL UTAUT AND UTAUT2 MODEL BY VENKATESH ET AL. (2003, 2012)

models to predict usage behaviour (Venkatesh et al. 2003). Venkatesh et al. found evidence for the moderating effects of gender, age, experience and voluntariness on determinants of behavioural intention: performance expectancy (similar to PU), effort expectancy (similar to PEOU) and social influence. Their model accounted for 70 percent of the variance and was therefore considered a substantial improvement over TRA, TPB and TAM (Figure 4) (Venkatesh et al. 2003). It is interesting to observe that voluntariness was found to be a significant moderator in the prediction of behavioural intention. This implicates that using TAM and UTAUT in mandatory environments may give unexpected outcomes. Venkatesh therefore extended UTAUT by adding three determinants for behavioural intention and testing it in a consumer context, UTAUT2. This extension proved to contain even more explanatory power than the original UTAUT.

Although TAM, UTAUT and their extensions are very popular within MIS research, they have two major shortcomings (Chuttur 2009). First, the Technology Acceptance concepts are mainly used in understanding intention and adoption behaviour. This implicates that the technology under study is still to be implemented. However, in business setting it is also valuable to investigate already implemented technology. Research suggest that usage of already implemented technology involves a behavioural attitude, like intention, but also a behavioural satisfaction (Au et al. 2002; Al-Gahtani & King 1999; Bharati & Chaudhury 2004). To investigate the determinants of actual usage behaviour of an already implemented technology, satisfaction may be more interesting to study than intention. Second, Technology Acceptance concepts are traditionally applied in consumer context. This context is characterized by a voluntary environment in which the user can decide whether to use the technology or not. However, in business setting the user is ordered to work with the technology at hand and does not have a real choice. As can be observed in UTAUT, research found support for the influence of voluntariness in technology acceptance, but it did not adjust the model for application in mandatory environments (Hwang et al. 2015). Current research will develop an adjusted model to account for these shortcomings. This will be extensively discussed in the next two paragraphs.



### 2.2.3 Technology Acceptance and Satisfaction

Although TAM and UTAUT focus on the attitude towards yet-to-be-implemented technologies, this research deals with an already-implemented technology. In this case, next to attitude towards such technology, satisfaction of the experience with the technology so far, are of interest. This paragraph will examine scientific research into technology satisfaction and the relation to actual usage, which will provide variables to incorporate in the conceptual model for this study.

In order to study technology satisfaction, psychology of human interactive responses must be studied. Al-Gahtani and King (1999) describe a general research model in which external stimuli

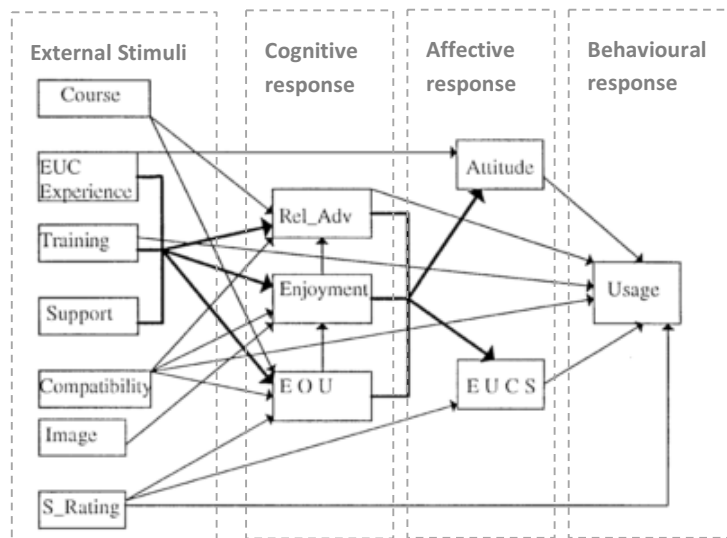


FIGURE 5: RESEARCH MODEL OF AL-GAHTANI AND KING (1999)

create a certain cognitive response in the form of beliefs and perceptions. This cognitive response triggers an affective response that exist of an attitude and a satisfaction towards the technology, both of which have direct influence on the behavioural response: usage (Figure 5) (Al-Gahtani & King 1999; Ajzen & Fishbein 1975). Al-Gahtani and King (1999) use this model to relate IT implementation factors (training, support, image, compatibility) to perceptions of relative advantage, enjoyment and ease-of-use, i.e cognitive responses, that in their turn affective responses like attitude and satisfaction and ultimately IT usage.

Nelson et al. (2005) also studied IT system satisfaction. But, they argued that data (or information) quality and system quality precedes satisfaction. They review data quality dimensions and system characteristics as antecedents that influence information and system quality, which ultimately determine satisfaction levels. In other words, they review system quality and data quality as independent variables that predict satisfaction levels, but they do not link satisfaction to actual usage of IT (Figure 6).

Usage of technology and the measurement of such has been frequently studied in literature. Most TAM-related research turns to self-reporting scales that measure perceived frequency and perceived purpose of use (Davis 1989; Venkatesh 2000; Al-Gahtani & King 1999; Wixom et al. 2005). (Straub et al. 1995) examined measurement methods of system usage and used a combination of subjective, self-reporting scales, as well as objective, factual usage observations. They found evidence indicating that TAM research that relies upon self-reporting scales may be artifactual and thus they recommend the use of factual computer-recorded observations or a combination of them.

Wixom et al. (2005) extended Nelson’s model and added a self-reporting scale to measure system usage. Similar to Nelson et al., they reviewed data quality as predictor of satisfaction and usage intention. In order to do so, they introduced the usefulness and ease of use variables from TAM research as behavioural beliefs explaining attitude (Figure 6).

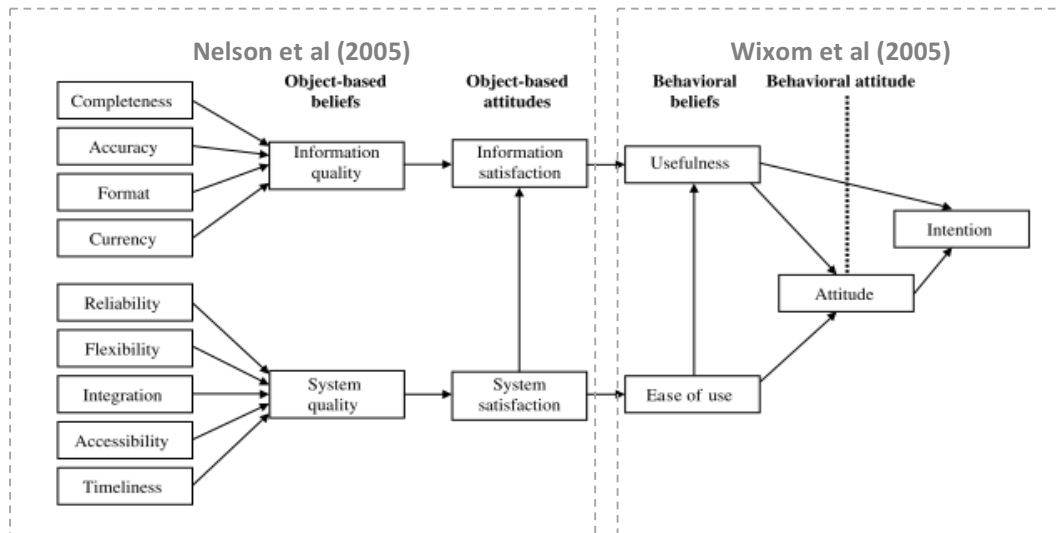


FIGURE 6: THE COMBINED RESEARCH MODELS OF NELSON ET AL. (2005) AND WIXOM ET AL. (2005)

Following from the work of Al-Gahtani and King (1999), Nelson et al. (2005) and Wixom et al. (2005), it becomes clear that studying satisfaction to explain usage behaviour is worthwhile, but the unit of analysis is usually observed only in the user of the data of the IT system. In other words, they measure the satisfaction level of the data consumer and link this to its (self-reported) usage of the IT system.

This thesis, however, aims at explaining data quality, by investigating the satisfaction and usage behaviour of data generators (providers). Surprisingly enough, literature does not provide any research in this direction. To lead research in this direction, this thesis argues, in correspondence to previous research of Al-Gahtani et al., that cognitive beliefs, Ease-of-Use and Usefulness (Enjoyment, Relative Advantage), of the data provider regarding the IT system, predict affective responses (Attitude, *End-User Computing Satisfaction*). However, in contrast to Al-Gahtani and King, current research argues that the perceived System Rating reflects data provider technology satisfaction and therefore is an affective response, instead of only a stimulus. Next, according to Wixom et al., Overall System Rating, i.e. labelled satisfaction in this research, is associated with actual usage and is referred to as Overall Satisfaction in the remainder of this thesis.

Different from earlier research, this thesis measures the factual quality of usage instead of usage frequency or usage purpose. If the studied usage is data generation, this implicates that measuring the quality of usage results in measuring the quality of data. Measuring data quality in DSS was explained in paragraph 2.1.

#### 2.2.4 TAM in Mandatory Environments

As explained in the introduction, the objective of this research is to identify predictors of quality of human generated data in Decision Support Systems (DSS). It also briefly mentions that DSS are widely used in businesses across various industries. As it is impossible to allow every individual employee to decide whether he wants to use organisational IT or not, IT usage is mandatory. In TAM research, an often-heard critique is its non-applicability in mandatory settings (Chuttur 2009). To account for the lack of mandatory application of the TAM model, Venkatesh & Davis (2000) in later applications incorporated business-related variables.

According to Hwang et al. (2015), who performed a literature review on TAM and its deviations in mandatory settings, technology usage behaviour in mandatory settings is not yet completely explained by current TAM methodology. They specifically mention the missing aspect of job security consequences. In other words, they observe a certain riskiness for the user of mandatory technology, as incorrect usage may have negative consequences for someone's job. TAM does not incorporate this facet of mandatory technology usage and thus is not completely applicable in business setting. Hwang *et al.* (2015) mention that:

*“an employee might have a negative attitude towards adopting the new system, but will ultimately use the system, because he/she has to and [feels that] no other option exists (Hwang et al. 2015 p.1278).”*

Interestingly, Hwang *et al.* describe a certain riskiness to reject the system although their attitude and/or satisfaction are negative. The decision of accepting or rejecting of a technology that is mandatory is found to be dependent on the (un)certainty of having obtained sufficient information to make the decision and the riskiness of the outcome of that decision.

Luckily, Davis and colleagues performed additional research that provided understanding of how humans deal with the perception of riskiness, which is closely related to the perception of (un)ambiguity. Venkatraman & Davis (2006) introduced the variables, perceived riskiness and perceived unambiguity, and found them to be important predictors of decision-making behaviour under uncertainty (Venkatraman et al. 2006). Perceived riskiness (PR) in their case is defined as a person's anticipatory value of his or her vulnerability to a loss by accepting a prospect. Perceived Unambiguity (PA) is defined as a person's perception of having enough information about the outcome of the prospect to accept the prospect. PR and PA have been found to be direct constructs in predicting the willingness to accept the prospects of a certain decision.

The writers claim that they are also usable in other decision-making under uncertainty (Venkatraman et al. 2006). Therefore, in this thesis, these two variables are added to the TAM variables to account for the decision to accept and use the technology under the uncertainty possible of job security consequences. It has been established that research in organizational IT usage has mandatory character, but it should also be emphasized that the unit of analysis of such research should shift from individual to team level. Next paragraph will elaborate on the notion of teams and team performance.

### 2.3 TEAMS AND TEAM PERFORMANCE

Modern organizations have heavily invested in project teams as a way of solving complex problems that exceed capabilities of single individuals (He et al. 2017). Therefore, in relation to the task of data generation, employees, often working in teams, use IT to accomplish their collective goals. Team-technology collaboration, therefore, depends very much on the team interaction process as team members influence each other heavily. In order to understand the team interaction process and performance, clarification about the notions of a *team*, *teamwork* and (*drivers of*) *team performance* needs to be established (Marks et al. 2001).

Current research on group dynamics defines a *team* as a social group of members that are characterised by a high task interdependency and shared and valued common goals (Salas et al. 2008; Forsyth 2014). In this sense, *teamwork* is defined as the coordination of the interdependent performance of work processes amongst team members. Successful teamwork leads to high team performance. *Team*

*Performance* is defined as the level of output of teamwork in terms of quality, efficiency and effectivity (Salas et al. 2008; Janz 1997).

To investigate team performance, Hackman and Morris (1975) developed a famous input-process-output (IPO) model of group performance (Figure 7). In this model, individual, group and environmental factors influence the group interaction process. Individual factors consist of member characteristics and attitudes. On the group level, organisational structure, size and cohesiveness are important factors (Mathieu et al. 2000). Environmental or external factors consist of everything else and can influence individual members or the group as a whole. Examples are reward structure, stress levels, organisational change and job security. Together, these three factors provide input for the group, or team, interaction process. Within this process, the team’s activities to accomplish certain goals are planned, executed and evaluate. Managing the interaction process involves mitigating interpersonal aspects, conflicts and commitment issues (Hackman & Morris 1975; Walton & Dutton 1969).

The output of teamwork is observable in tangible and intangible results, or in other words ‘hard’ performance outcomes and ‘soft’ other outcomes. Interestingly, member satisfaction is one of the ‘soft’ outcomes that is taken into account in team research and corresponds to technology satisfaction in TA research, as is explained in last section. ‘Was the objective reached’, ‘what was the quality of the solution’, ‘how quick was the solution developed’ and ‘what was the number of errors made’, are questions determining the tangible output performance. However, intangible output is more difficult to observe. ‘How did the team’s cohesiveness change’, ‘what is the member satisfaction about the task or tools’, ‘did attitudes change’ etc. In TAM research, it can be observed that the individual satisfaction and attitude-change actually precede performance outcomes. This may also be the case in teamwork. Therefore, this thesis is investigating the output of team interaction process as a sequence of affective outcomes that influence performance outcomes.

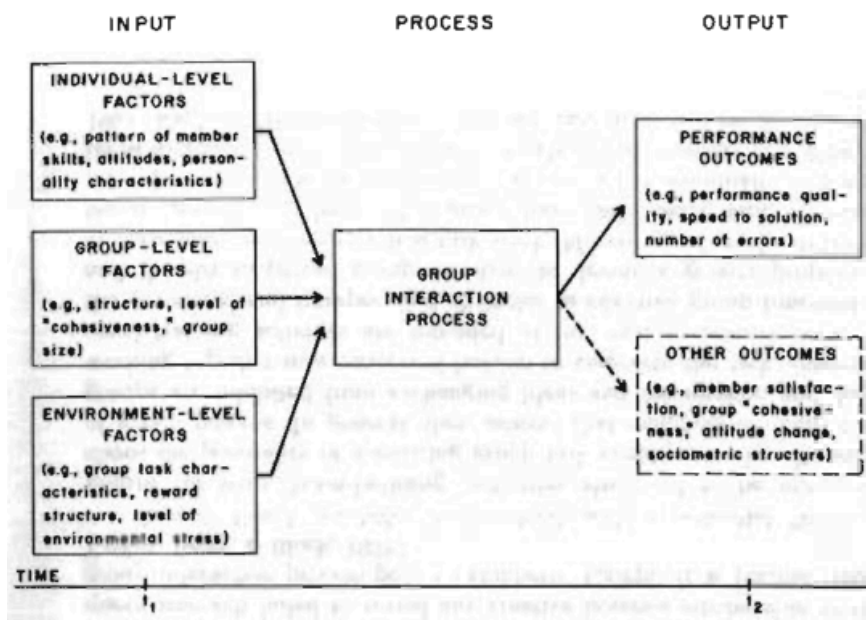


FIGURE 7: INPUT-PROCESS-OUTPUT MODEL PROPOSED BY HACKMAN AND MORRIS (1975)

With the IPO model, it becomes clear how team performance is influenced by the input factors and interaction process. More contemporary research has investigated drivers of team performance. Salas *et al.* (2008) identified several of them. Firstly, *team or shared cognition* is a critical factor for team performance,

in achieving high quality, efficiency and effectiveness (Salas et al. 2008; Mathieu et al. 2009). Team cognition refers to the mental models, in the form of rules and agreements, collectively held by a group of individuals that act as a coordinated unit in pursuit of accomplishing a common task (He et al. 2017; Mathieu et al. 2009). Secondly, they argue that team training promotes team work and stimulates team performance. Team training aligns competences amongst team members and it stimulates shared cognition (Kukenberger et al. 2015). Thirdly, team composition (personalities, motivation and cultures) and work structure (norms, communication and workload) have influences on team effectiveness and team performance. Fourthly, knowledge sharing management is of importance as team members need to share and utilize their unique knowledge to successfully accomplish a task (Choi et al. 2010). Lastly, the influence of well-designed technology on team performance is emphasized as facilitator of high-level interaction and collaboration of teams and Information Technology (Majchrzak et al. 2005; Choi et al. 2010; Maruping & Magni 2015).

Conclusively can be stated that the influence of technology acceptance and satisfaction on the quality of human generated data in corporate, I4.0 businesses, i.e. data-sensitive, mandatory environments, should be done at the team level. Therefore, TAM results at individual level need to be aggregated to team level, which is something that thus far has not been investigated in IS literature.

## 2.4 CONCEPTUAL FRAMEWORK AND HYPOTHESES

Against the background of the Industry 4.0 concept and its dependence on data, there is a need for investigation into the predicting factors of human generated data quality. This thesis aims at providing understanding of these factors by investigating team-technology acceptance and satisfaction in mandatory environments. Chapter Two examined the concepts of DSS and data quality dimensions. It also examined TAM research and team performance theory. The combination of these concepts leads to a conceptual model that is the basis for this research. The study will focus on the effect of team-technology acceptance on the quality of human generated data in Decision Support Systems (Figure 8). In particular, this thesis will examine data quality only on the bases of data consistency.

In the first version of TAM, Davis et al. (1989) found a positive effect between PEOU and PU. In other words, they found that the user perception of usefulness, depends on the perception of ease to use the program. Al-Gahtani and King (1999) found evidence that supports the claim that PU, which they call enjoyment, moderates the effect of PEOU on relative advantage. In this thesis, the moderating effect of PU on the relation between PEOU and Overall Satisfaction is hypothesized.

- **H1. Perceived Ease of Use of the DSS has a direct effect on perceived usefulness and perceived usefulness will moderate the relationship of perceived ease of use and the overall satisfaction.**

In their research Al-Gahtani and King (1999) introduced the user's perception of overall system quality as an external stimulus, which they called Rating. They also used the *End-User Computer Satisfaction (EUCS)* variable as an affective response. However, except a positive correlation with Rating, the EUCS variable was not significantly correlated with any other variable. This study does not agree with the qualification of Rating as an external stimulus, because Perceived overall system quality also is a measure of satisfaction and thus an affective response. Therefore, it is hypothesized that perceived overall system quality, in this thesis mentioned to as Overall Satisfaction, is preceded by the constructs of belief and perception, i.e. Perceived Ease of Use and Usefulness.

- **H2. The more a team perceives a DSS as easy to use, the higher the overall satisfaction with the technology.**
- **H3. The more a team perceives a DSS as useful, the higher the overall satisfaction with the technology.**

Al-Gahtani and King (1999) found evidence for a positive relation between System Rating and System Usage. Their System Rating item consisted of a single item that measured the overall satisfaction of the user towards the technology. In TAM research, this is usually studied with self-reporting scales that measure the intention to use a technology, but also the frequency and moment of usage (Straub et al. 1995; Venkatesh 2000; Davis 1989). However, quality of usage, a third variable of the usage construct, is often neglected. Yet, in light of the growing focus on data analytics and data quality, quality of technology usage is of high importance (Nelson et al. 2005). Quality of DSS usage by data providers results in a level of quality of input data the deliver. Therefore, the usage construct in this thesis is build up by the four dimensions of data quality, of which, due time constraints, only the consistency variable is chosen to be studied. In accordance with Al-Gahtani and King, the Overall Satisfaction is hypothesized to have a positive direct relation with DSS usage and thus DSS data consistency.

- **H4. The higher a team's satisfaction with the DSS, the more consistent the data will be.**

In current research, the team-technology acceptance is studied in a mandatory environment. Therefore, cognitive responses like PU and PEOU may not explain usage quality entirely (Hwang et al. 2015). Therefore, as explained, this thesis uses the decision-making under uncertainty variables, perceived unambiguity and riskiness from the research of Venkatraman et al. (2006). Perceived unambiguity is found to be a strong predictor of technology adoption (Barham et al. 2014). Common sense can relate to this, as it is logically defendable that when a technology is perceived unambiguous by the users, the adoption of that technology is more likely. In accordance with this, current research hypothesizes that:

- **H5. The more a team perceives the use of a DSS as unambiguous, the more consistent the data will be.**

Perceived riskiness was used in combination with TAM by Featherman and Fuller (2002). They hypothesized, and found significant support, that potential technology users have reduced adoption intentions when they perceive a certain technology riskier, i.e. they perceive greater potential losses as consequence of adopting the technology (Featherman & Fuller 2002; Featherman & Pavlou 2003). In accordance with this, it is hypothesized that as data providers have a higher perceived riskiness towards an, already-implemented DSS, the data they provide will be of lower quality.

- **H6. The more a team perceives the use of a DSS as risky, the more inconsistent the data will be**

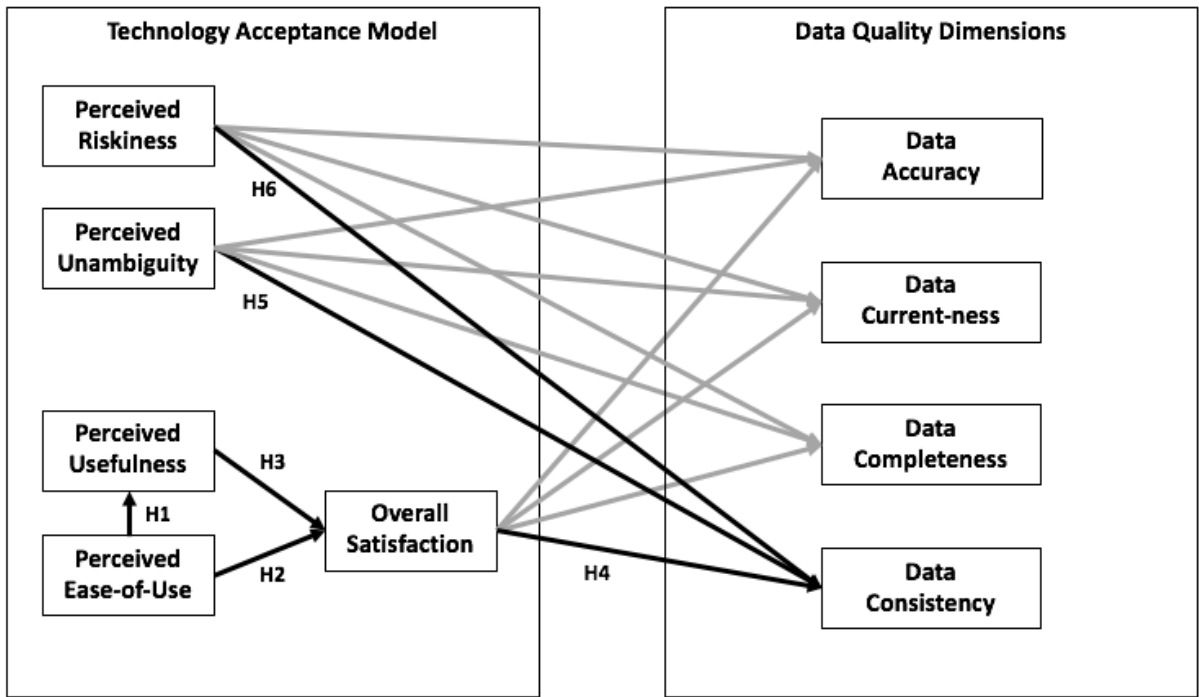


FIGURE 8: RESEARCH MODEL

## 2.5 CONCLUSION

In this chapter, the key concepts of Data Quality in Decision Support Systems, Technology Acceptance and Satisfaction and Team Performance were explained by examining various sources of literature. It is important to bear in mind that this research studies the cognitive responses of the providers of DSS data, not the consumers of data. If consumers of data were the focus of this research, data quality would be reviewed as external stimulus and predictor of cognitive responses. By combining the theoretical concepts, several initial hypotheses that explain the effect of team-technology acceptance on data quality of DSS were posed. In the remainder of this thesis, these six hypotheses will first be validated by interviews with managers that experience technology acceptance consequences daily. Next, the validated hypothesis will be tested through Structural Equation Modelling.

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### 3 METHODOLOGY

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This chapter will explain the rationale behind the research design and will discuss selection of methods that ensure a rigor and sound research to study the effects of team-technology interaction on to DSS data quality levels.

#### 3.1 RESEARCH DESIGN

This research will address the potential correlation between technology acceptance behaviour in mandatory environments and data quality levels. This will be done using a multimethod comparative field study. Conducting ‘*field research*’ is about studying the effects of a phenomenon in its natural setting or place. When the field research involves the comparison of the phenomenon at two or more locations, this is called a *comparative field study research*. The comparative field study design is chosen to give the research external validity and to aim for a practical significance (Kaarbo & Beasley 1999). To ensure internal validity, *methodological triangulation*, defined as the combination of multiple methodologies studying the same phenomenon, was pursued (Jick 1979; Denzin 1978).

#### 3.2 METHOD SELECTION

This multimethod approach for investigating the team-technology satisfaction exists of exploratory interviews at Royal Vopak, which is the case company in this research. The interviews will validate the hypothesis from literature and they will provide understanding of the DSS INFOR and input for the data quality assessment (Figure 9).

In the first phase, the main objective of the interviews is to explore cause variables and verify the variables offered by TAM and a proxy for the DSS integrity assessment. The interviews also will be used to translate the abstract concepts of technology acceptance and DSS, to a specific case. In practice, the interviews provide verification by the business for the variables from scientific TAM literature. This should increase the practical relevance of the study. The second phase consists of a survey and a data quality assessment of the INFOR DSS. The survey will use the commonly used TAM variables (Davis 1989; Venkatraman et al. 2006). A quantitative data analysis of pre-existing DSS data will be conducted through a proxy to measure the current level of data integrity as part of data quality. In the third phase, the results from the survey and DSS data quality assessment were analysed with Structural Equation Modelling technique (SEM) to test the hypotheses.

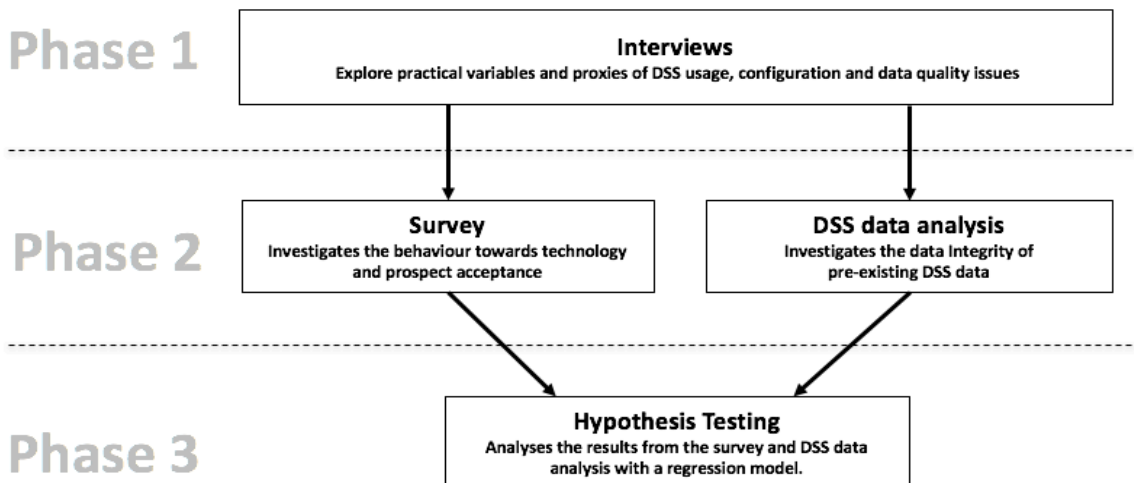


FIGURE 9: RESEARCH DESIGN

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## 4 PHASE 1: EXPLORATORY INTERVIEWS

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### 4.1 CASE STUDY COMPANY

#### 4.1.1 Royal Vopak

Royal Vopak is a petrochemical storage company that offers a logistical service in the petrochemical supply chain. Although its history dates back to the early 17<sup>th</sup> century, under its current name Vopak was founded in 1999 by the merger of *Pakhoed* and *van Ommeren*. Vopak focuses on storage of bulk material from the oil and chemical industry and is the world's leading independent tank terminal operator. Their network of 67 terminals in 27 countries across all continents is located near ports at strategic points alongside the petrochemical trade routes. According to their website, Vopak's strategy focuses on 4 pillars: i) growth leadership, ii) operational leadership, iii) customer leadership and iv) a sustainable foundation. In the value chain Vopak positions itself in two ways. First, when liquid or gas petrochemicals from offshore platforms arrive at shore. Secondly, after raw products have been processed in refineries, they are shipped to customers. Vopak's main service is storage of liquid bulk products. However, often, additional handling for optimal storage is provided. Examples are blending of products, mixing additives and applying protective nitrogen blankets over chemical products and heating or cooling products for (un)loading to ships, railcars or trucks. Last, Vopak assists its customers in documentation and planning of ship departure, arrival and (un)loading. Vopak is organised in a matrix structure divided in five divisions: NL, ASIA, EMA, AMERICAS and CHINA. Locally, tank terminals have autonomy. They have their own balance sheet, income statement and management and they perform their own sales, and operations. Global directors of specific domains are involved in monitoring, stimulating and innovating tank storage operations regarding for example: procurement, HR, IT etc.

The argumentation behind the selection of Vopak as the subject of this research is twofold: Firstly, Vopak is one of the early adopters of I4.0 principles in the traditional/conservative petrochemical industry. With the appointment of its first Chief Information Officer (CIO) in 2014, Vopak started to investigate a possible digital transformation. His vision on digitalisation is focused on the implementation of Internet of Things principles to digitalize and innovate tank terminal operations. The new CIO emphasizes the role of human and their behaviour in this transformation and specifically mentions the convergence of IT and OT departments (van der Schaaf 2016). There is a certain commitment, which benefits the feasibility of the project. Secondly, Vopak's core business exhibits characteristics from different industrial business activities: they exhibit logistical characteristics regarding planning and scheduling of logistics such as storage and transport, also they perform petrochemical processing activities by treating or blending the products for storage optimization. These overlapping activities make Vopak a proxy for a wide array of companies.

### 4.2 SAMPLING

To gain deeper understanding in the maintenance process and role of the INFOR DSS and the variables causing DSS acceptance (TAM), three interviews were conducted. In this section, the sampling technique and subjects, the procedure and the interview protocol are explained. In Appendix D, E and F, the interview summaries with validation signature can be found.

The interviews were explorative in nature. To identify presumptions, perceptions and insights from different backgrounds, interviewees A and B were chosen on the IT/Business side of the INFOR program,

whereas interviewees C was from the Operations side of the maintenance process and the INFOR program. The IT/Business side oversees the basic functionality of INFOR. The so-called application managers and global or divisional key users that were interviewed, were responsible for complaint handling, program failure fixes and user training. The maintenance engineers from the operations side of the program, use the data from INFOR on the one hand for the day-to-day overview of maintenance activities, but also in order to analyse and optimise the maintenance process or the equipment in general. This process of sampling is judgmental in nature as subjects were deliberately chosen because they represent a certain population and origin of issues (Higginbottom 2004).

### 4.3 PROCEDURE

The interviews were conducted using a semi-structured interview protocol, which means that there were general topics that predetermined the topic of conversation (Yin 1994). Therefore, only the first question was predetermined. A general interview guide with topics, questions and probes was developed. The three interviews were conducted in the lobby of Vopak headquarters in Rotterdam.

The general procedure for the interviews started with explaining the exploratory purpose of the interview and addressing confidentiality by ensuring anonymity. Next, the format and duration of approximately 45-60 minutes were mentioned. After the interview the interviewee was informed about future references and contact details.

The line of questioning within the guided interview approach was semi-predetermined. The line of topics consisted of three phases: first of all, the interviewee was asked: *“How is the maintenance process structured?”* This was an easy question to lighten the mood, but it also initiated an open conversation about the way the Vopak maintenance process from the point of view of the interviewee. In this stage, subtle words or phrases could indicate a certain stance towards the process or program. Next, the topic of the interviewee’s experiences with INFOR was initiated with the question: *“What are your experiences with INFOR in relation to the maintenance process?”* After this, the last topic of interest was the interviewee’s perception regarding the opinions of other INFOR users. This was initiated with the question: *“To what extent do you think your opinions are shared by other INFOR users?”*

Each first answer to a new question was then build upon with a combination of sub-questions and probes. Sub-questions were not predetermined but the interviewer had a short list with noted questions to guide a follow-up question on the topic of his interest. The predetermined types were based upon the work of Michael Q. Patton (2003):

1. **Action:** what the interviewee was doing or is doing?
2. **Opinion/values:** what the interviewee thinks about the things he/she is doing?
3. **Feeling:** To what extent does a certain opinion activates a certain feeling?
4. **Knowledge:** This is just fact-checking and consists often out of closed questions.
5. **Sensory:** To identify whether the interviewee has experienced a certain opinion or action himself or it was seen or heard.
6. **Background:** to identify the relations between certain claims and the background of the interviewee.

Next to these six question types, five probes were listed to remind the interviewer how a more thoughtful, thorough response could be elicited:

1. **Silence:** It leaves an 'awkward' silence in which the interviewee might clarify his response.
2. **Overt encouragement:** This might be vocally (e.g. uh-huh or OK) or non-vocally (nodding or waving hands).
3. **Elaboration:** Start a sentence or line of thought and let the interviewee finish it.
4. **Clarification:** Ask the interviewee to clarify something he said earlier before.
5. **Repetition:** Repeat the same question in a different wording. If the interviewee gives the same response it is more consistent.

The interviews aimed at gaining in-depth knowledge of the underlying presumptions, perceptions and issues towards DSS technology acceptance. During the interview the interviewer took notes, which were used to write a short summary of every interview. The summary was then send to the interviewee for validation of statements for approval. The summaries provided insights, variables and proxies for the survey and DSS data analysis. Next section will discuss the results of the interviews in the form of a detailed case story, that consists of a description of the maintenance process at Vopak. Secondly, it contains a detailed examination of the role of INFOR in the maintenance process and specific errors and issues that hamper further development of the program. Lastly, it provides a collection of expectations and presumptions regarding the user-opinion towards INFOR as causes to the errors and issues identified.

## 4.4 CASE DESCRIPTION

### 4.4.1 The Maintenance Blueprint

The Vopak maintenance Blueprint accounts for both the preventive and the corrective maintenance process (Figure 10). The corrective maintenance process is handled by the Operations (OPS) group within the terminal. OPS is responsible for continuous monitoring of the equipment and solves incidents themselves or assist contractors. Members of the OPS team perform different tasks like monitoring and repairing, but they have a common goal of resolving maintenance issues. Because of the different tasks they perform, they experience a high task interdependency between the different members. In total, the process consists of nine tasks ranging from incident detection to work order (WO) closing (Appendix A).

It all starts with the detection of an incident. Incidents can happen during inspection rounds, but can also be based upon sensor data. In either way, an engineer is physically present at the location of the incident to inspect the malfunctioning equipment. Normally the operator would write down the details of the incident, although at some terminals they already work with handheld devices that afford the operator the possibility to directly open a work request. In the written case, the operator returns to his office and starts the filling a work request. Next, a supervisor, usually a more experienced operator/engineer, reviews the request. The review has three possible outcomes: First, the request is valid and is sent through for planning and scheduling. Second option: the request, for some reason, is not valid. In this case, the request is ignored and nothing will happen. The last possibility is that the request is not complete and lacks information. The supervisor cannot make an adequate decision and will sent the operator back to retrieve the missing information. In case of the first option, the request is sent to the planner and scheduler – which are two separate tasks that are performed simultaneously. The planner estimates the necessary time, workforce, tools, parts, etc. for the maintenance execution. Simultaneously the scheduler selects the starting date and work days for the execution. After these steps, a supervisor checks the readiness of the project. Again, the three options apply, although the last option of cancelling the maintenance works is seldom necessary in practice. But if so, the supervisor arranges the necessary permits. Then, they either

solve the incident themselves or to assist a hired contractor. After the execution, a supervisor checks the results of the maintenance and assesses if there is additional action required or not. If not, he instructs the planner to determine the actual duration, costs, tool usage, etc. When all this administrative information is retrieved, and stored correctly, the end responsible terminal maintenance manager reviews the complete work request and administration. He ultimately closes the request.

The objective of the maintenance process is to perform safe, secure, good, cheap and fast maintenance. In terms of safety, the process is designed in an agile manner, which means that multiple feedback loops ensure close monitoring of the process. In practice this results in multiple checks by supervisors have to detect possible safety hazards in an early stage. To create a secure maintenance process, different people perform different roles are supposed to be filled in by a different person (multiple pairs of eyes survey the works). The close relation between the OPS and TS teams should improve the maintenance works. By analysing the frequency of malfunctioning equipment and the natures of failure and cause, future incidents might be predicted and maintenance could be scheduled more conveniently, at reduced cost. Physical proximity of the different roles on the terminal, should ensure fast information sharing at the terminal with faster throughput times of maintenance requests.

Although these objectives are clear and straightforward, several complexities exist. First of all, at most terminals the different roles are owned by the same persons. This potentially endangers the safety and security of the maintenance, because underlying reason for this, is that some terminals do not have enough employees to fill every role with a different person. Another reason is that the process speed increases if the same person can do several tasks at once. A second complexity in the process is based in the fact that the feedback loop in reality is almost never invoked, because every role expects the next in line to do so. Moreover, invoking a feedback loop means a time delay in the maintenance. Maintenance KPI's are heavily focused on throughput times and not on quality of administration or actual maintenance. Third complexity can be observed in the fact that maintenance managers take a long time to actually review the maintenance execution and close it, because the maintenance works are already performed and the incident is already resolved. Therefore, there is less pressure to finish the cycle.

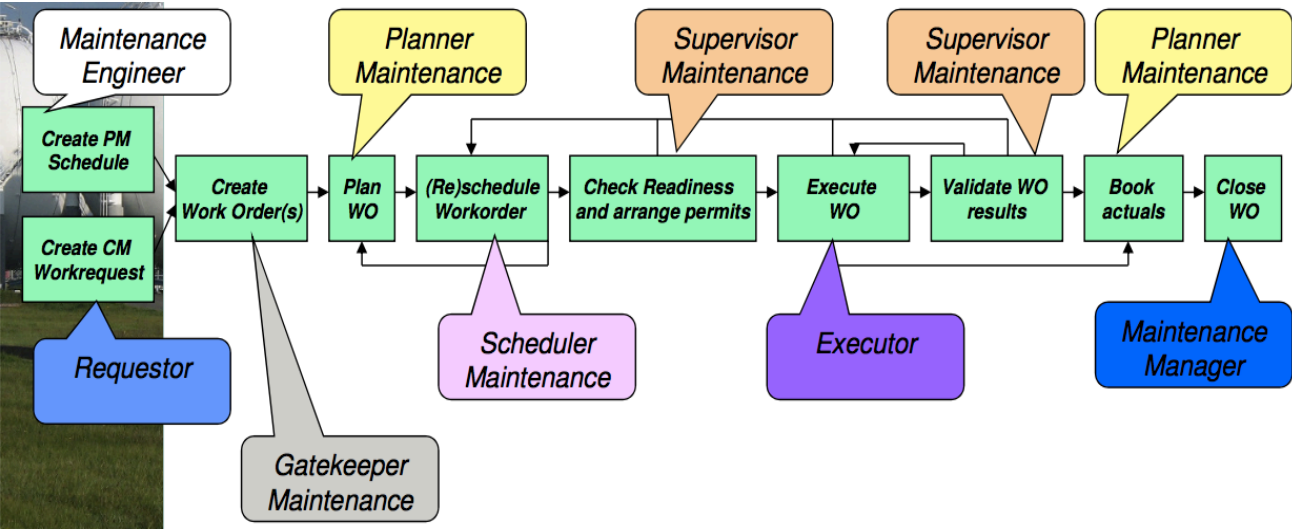


FIGURE 10: VOPAK MAINTENANCE PROCESS FLOW DIAGRAM (SOURCE: VOPAK MAINTENANCE STRATEGY)

#### 4.4.2 The Role of INFOR in the Maintenance Process

INFOR is the enterprise asset management (EAM) program Vopak uses to manage the maintenance process described above. Its main purpose is to afford users the possibility to store, analyse and visualise maintenance records. INFOR usage can be observed in two components: documentation and configuration.

When INFOR was acquired in 2008, it was customized to fit seamlessly onto the blueprint. INFOR was purchased in a default mode. As a result, the database of equipment and linked information class, severity details, codes, location and general characteristics, had to be configured per terminal. Every terminal works with slightly different parts from local suppliers – i.e. they have the responsibility to maintain the configuration of their own equipment. When a certain piece of equipment requires maintenance and a work request is created, the linked information immediately is filled in in the log file. Therefore, it is very important to initially configure new equipment correctly and completely.

Documentation entails the logging of work requests. In last section, the blueprint of the Vopak maintenance process was explained. In the first of the nine tasks, the operator has a work request and thus creates a work order (WO), a log file in which all necessary information regarding the work request can be logged. One work order has eight tabs: record view, comments, activities, book labour, closing, parts, cost summary and other costs. The record view tab is an overview tab that displays most information or most important fields from the other tabs (Appendix B). The operator starts with entering the first information regarding the location, equipment, problem description, several codes and necessary comments. These first entries are mandatory. After the creation of the WO every role in the process has the responsibility to check the entries of its predecessor and add information from its own task. As a result, the WO gets filled gradually and multiple eyes monitor the process.

Data from INFOR is used for long term (predictive) analysis: first, every WO requires the logging of four standardized codes that explain the nature of the problem, failure reason, identified cause and actions taken. These codes are analysed to determine the most frequent problems, failures and causes per equipment and what actions are mostly performed to solve them. The options for problem and failure codes are dependent to the class of the equipment. Therefore, every piece of (new) equipment used at the terminal has to be correctly linked to a class. Cause and action codes are general and not linked to class. They are configured by the application manager and they are the same for all terminals worldwide. Second, every WO receives a certain priority level that gives the maximum duration of the maintenance works. It is of the terminals interest, what percentage of maintenance works is done within the time limit. Globally, this can be done to identify strongly performing terminals to learn from their best practises. Thirdly, analysis focusses on better identifying maintenance costs. Maintenance is one of the costliest activities of the Operations Department. However, it proves hard to accurately determine direct and indirect costs. When labour and material costs are carefully logged, large scale analysis of maintenance costs per type of equipment, location or running time, can be performed and can provide valuable insights in the maintenance cost allocation. Next to these three examples there are several more analyses performed and there are a lot more possibilities to use INFOR data.

Yet, in practice INFOR data still contains errors or misses input. Poor data quality is observed in documentation as well as in configuration: WO documentations are not filled completely or are filled in illogically and inconsistently. Equipment is not or inconsistently configured to end-positions, classes or severity levels. In other words: data quality levels thus hamper the effective usage of big data for maintenance analysis. Although causes for this poor data quality are not known, some presumptions and perceptions exist.

### 4.4.3 Perceptions and Presumptions towards INFOR

The interviewees were consistent about the causes for poor data quality.

First of all, the daily users of INFOR lack a sense of the broader utility of the program. The presumption resulting from the interviews was that most operators review INFOR only as a day-to-day tool, that is laid upon them by higher management – without recognizing the added value of the program for their own activities (Usefulness). Secondly, the interviewees mentioned unreachable or unfindable support as a cause for poor data quality. In theory, support can be received from the terminal and divisional key users, or by directly sending an email to the application manager. Nevertheless, people may not know who the terminal or divisional key user is. Moreover, it was suggested that the motivation to use INFOR correctly may be low due to the fact that small mistakes do not seem to have immediate impact onto the operation (Riskiness). Thirdly, it is expected that the knowledge to use the program is not up-to-date anymore (Ambiguity). In the last decade, new employees started working with INFOR, while older employees may find it hard to understand and teach the program to new employees. Lastly, interviewees referred to complaints about non-user-friendliness of the program have been heard. Although the interviewees did not experience this themselves they presume a reluctance to the program, because it takes more time, effort and mental capacity to use it correctly than to use it only for day-to-day activities (Ease of Use).

It is important to emphasize that the presumptions about the INFOR perception, are mere presumptions. Large scale surveys and validating research have not been conducted. To determine de weight and existence of these presumptions, research should validate them and correlate them to data quality levels.

## 4.5 CONCLUSION

This chapter presented the first phase of this research: a number of exploratory interviews at Royal Vopak examined the maintenance process and the software application support, or decision support system, INFOR. It also identified existing issues and presumptions regarding the DSS, with which the variables derived from literature were validated with the business. From the interviews, it was derived that usefulness, usability (EoU), ambiguity and risk aversion, are four presupposed factors of IT usage and data consistency, which are also experienced by business. Therefore, it can be concluded that the theoretical hypothesis from Chapter 2, are also practically valid. It was also established that the coding activity of incident failure, problem, cause and action is a good proxy to measure data consistency. Lastly, the interviews provided evidence that the terminals could be observed as teams. Group members from OPS have high task interdependency in resolving maintenance issues, which is their common goal, and thus the members from OPS can be considered a team. Next chapter will describe phase two of this research.



## 5 PHASE 2: SURVEY AND DSS DATA ANALYSIS

The second phase of this research uses the results from the literature review and the understanding and insights derived from the interviews as input for development of the survey instrument and DSS Data Quality Assessment. This chapter will discuss the participants and sampling, study procedures, measurement scales and the results of both the survey and quality assessment.

### 5.1 PARTICIPANTS AND DATA SAMPLING

The survey was distributed to a total population of 786 employees from 23 terminals across 4 divisions worldwide: three in the Americas, eight in Asia, six in EMEA and four in the Netherlands (NL) (Table 1, terminals are replaced by letters to ensure anonymity). All employees from this sample worked at terminals that used INFOR from 2014 until the end of 2016. The overall response rate was 18%, or 143 respondents from 23 different terminals and 4 different divisions (133 men, 10 women, *Mage* = 41-50) (Table 1).

For the quality analysis, DSS data from the same 23 terminals as for the survey was retrieved for examination. Pre-existing DSS data was collected at those terminals with the additional restriction that only the corrective work orders were examined. This is due to the fact that Vopak mainly focuses on the costly corrective maintenance. The obtained dataset contained 69132 work orders (Table 1).

TABLE 1: SAMPLE STATISTICS

Divisions & Terminals	Total Send	Respondents	Response rate	Total Work Orders
<b>AMERICAS</b>	<b>113</b>	<b>24</b>	<b>21%</b>	<b>8353</b>
a	76	19	25%	7736
b	19	2	11%	373
c	18	3	17%	244
<b>ASIA</b>	<b>133</b>	<b>23</b>	<b>17%</b>	<b>13161</b>
a	16	2	13%	1695
b	14	2	14%	536
c	16	5	31%	1655
d	17	2	12%	683
e	14	4	29%	882
f	15	2	13%	2053
g	18	4	22%	1436
h	23	2	9%	4221
<b>EMEA</b>	<b>156</b>	<b>49</b>	<b>31%</b>	<b>19653</b>
a	29	11	38%	5232
b	17	10	59%	4110
c	37	11	30%	1865
d	19	3	16%	2014
e	38	9	24%	4193
f	16	5	31%	2239
<b>NL</b>	<b>384</b>	<b>47</b>	<b>12%</b>	<b>27965</b>
a	71	14	20%	5657
b	36	4	11%	2202
c	43	4	9%	2771
d	48	7	15%	5316
e	147	16	11%	10123
f	39	2	5%	1896
<b>Grand Total</b>	<b>786</b>	<b>143</b>	<b>18%</b>	<b>69132</b>

## 5.2 PROCEDURE

### 5.2.1 Survey Procedure

The initial respondents received the survey through an email with a link to Google Forms. The email did not contain any information about the nature of the questions or an explanation of the variables and constructs, but it explained the objective of the research:

*In our continuous curiosity of the opinions and perceptions towards the software we use and develop, we would like to know how you think about the INFOR program. This survey is part of an ongoing research that aims at creating a deeper understanding of your opinion towards INFOR and how you use it.*

The surveys were open for responses for two weeks and after one week the DSS manager sent a reminder. Participation was voluntary, but to motivate respondents, four electronic gadgets in the form of an electronic personal assistant devices (Amazon Echo Dot) were raffled and are distributed to the winners after completion of this thesis. This was all explained in the introduction of the survey. Every section of the survey contained an open item in which respondents could describe additional information relating to the variable of that section or relating to the survey itself.

### 5.2.2 DSS analysis Procedure

The dataset was retrieved directly, correctly sampled, from the DSS: INFOR. In Chapter 4 the interviews provided a detailed explanation of INFOR and its applicability in the maintenance process. In Chapter 2, the concept of data quality was examined. It was established that data quality as a whole can only be observed in longitudinal studies (see also the discussion on future research in Chapter 7). Therefore, due to time constraints, this research only performs a data consistency assessment. This research focused on consistency by investigating the problem, failure, cause and action codes as a proxy for the data quality of the rest of INFOR. This proxy was identified during the interviews with the application manager, global key user and maintenance manager, summarized in Chapter 4. The retrieved data was analysed using Excel. Pivot tables were used to find the number of cases in which the OTHER code was chosen. From this, percentages per terminal were calculated. The results of the analysis were reviewed in percentages of correct cases, i.e. non-OTHER-coding. Although a certain percentage of OTHER coding may be valid, it is in the interest of data analysis not preferable (see Appendix D, E and F). Therefore, for the present research the percentage of non-OTHER coding was assumed to represent the overall level of data consistency of the DSS technology, INFOR.

## 5.3 MEASUREMENT SCALES

As explained in Chapter 2, TAM research and literature provided validated questionnaires that explained behaviour towards accepting of a technology and a certain prospect. Literature in data quality delivered dimensions that measure data integrity. In this paragraph the constructs, their corresponding variables and the items will be further explained.

### 5.3.1 Perceived Riskiness

The perceived riskiness (PR) measure was used to measure a person's anticipatory appraisal of his or her vulnerability to a loss by accepting a certain prospect, in this case the prospects of a certain technology

usage (Venkatraman et al. 2006). Four items measure PR: “How risky is it to use [INFOR], It is very likely that I will lose on-the-job performance, if I use [INFOR].” “If I use [INFOR], I worry about the consequences.” and “I could incur a great loss if I use [INFOR].” The measures, except the first one, all have a 7-point Likert scale with anchors ranging from 1 (*Strongly Disagree*) to 7 (*Strongly Agree*). The first question ranged from 1 (*very safe*) to 7 (*very risky*; Cronbach Alpha: 0.80).

### 5.3.2 Perceived Unambiguity

The perceived unambiguity (PA) measure was used to measure a person’s perception of vagueness of the probabilities of the outcomes of a technology’s prospects due to lacking information (Venkatraman et al. 2006). In correspondence with prior research, four items measure PA: “I fully understand the distribution of the outcomes of [INFOR].” “I have all the relevant Information I need to use [INFOR].” “I have sufficient Information to use [INFOR].” “I need more Information to use [INFOR].” The measures had the same 7-point Likert scale as with PR: 1 (*Strongly Disagree*) to 7 (*Strongly Agree*; Cronbach Alpha: 0.54).

### 5.3.3 Perceived Usefulness

Perceived Usefulness (PU) was adopted from Davis (1989) and measures the degree to which a person believes that using the technology would enhance his or her job performance (Davis 1989). Items to measure PU were: “[INFOR] improves my job performance.” “[INFOR] increases my productivity.” “[INFOR] enhances my effectiveness on the job” “Using [INFOR] makes it easier to do my job.” “I find INFOR/ME2 useful in my job.” The items to measure PU were anchored on a 7-point Likert scale as 1 (*Extremely Unlikely*) to 7 (*Extremely Likely*; Cronbach Alpha: 0.94).

### 5.3.4 Perceived Ease-of-Use

Also, the perceived ease-of-use (PEoU) measure was adopted from Davis (1989). It measures the degree to which a person believes that using a particular system would be free of effort (Davis 1989). The items measured PEoU were: “I find [INFOR] useful in my job.” “I would find it easy to get [INFOR] to do what I want it to do.” “My interaction with [INFOR] would be clear and understandable.” “I would find [INFOR] flexible to interact with.” “I would find [INFOR] easy to use.” “It would be easy to use [INFOR] correctly.” The items had the same 7-point Likert scale as with PU, with anchors ranging from 1 (*Extremely Unlikely*) to 7 (*Extremely Likely*; Cronbach Alpha: 0.85).

### 5.3.5 Overall Satisfaction

This variable was adopted from the work of Al Gahtani and King (1999), who also used a single item question to assess Overall Satisfaction with the DSS program as a whole. This measure was a single-item scale: “What is your overall experience with [INFOR]?” The item has a 10 point Likert scale (from 1 to 10).

### 5.3.6 Data Consistency

Data consistency is measured as the percentage of non-OTHER entries in the problem, failure, cause and action codes. A high level of OTHER codes is an inconsistency as it is not logical, as was established in the interviews. Consistency was presented in percentage of correct data per terminal (team).

## 5.4 PRE-ANALYSIS

This section will elaborate on the measurement and pre-analysis of this research. First, it will give the descriptive statistics of the survey and DSS data analysis. Next, it will show the results of a principal component analysis that confirms that the items correctly load on the theorized variables. Then, a correlation matrix was developed to test the correlation between TAM variables and Overall Satisfaction. After that the Intra Class Coefficient was determined in order to establish the feasibility of aggregation of individual survey results to team (terminal) level.

### 5.4.1 Descriptive statistics

In table 2 the survey descriptive statistics per item are given. The items within the four TAM variables can be considered normally distributed (Skewness = -1.04, 0.83, Kurtosis = -.99, 0.18). In Table 4 the results of the data consistency ( $M=40\%$ ,  $SD=15\%$ ) assessment are given. The results are given in percentages that state the level of complete or consistent Work Orders (WO's). Abbreviations represent the different terminals (teams) arranged by division.

TABLE 2: SURVEY DESCRIPTIVES (N=143)

	Mean	Std. Deviation	Skewness	Kurtosis
<b>Perceived Riskiness</b>				
How risky is it to use INFOR/ME2?	2,37	1,36	,580	-,638
It is very likely that I will lose on-the-job performance, if I use INFOR/ME2.	2,91	1,69	,469	-,743
If I use INFOR/ME2, I worry about the consequences.	2,56	1,60	,588	-,749
I could incur a great loss, if I use INFOR/ME2.	2,36	1,45	,825	-,097
<b>Perceived Unambiguity</b>				
I fully understand the distribution of the outcomes of INFOR/ME2.	4,73	1,56	-,516	-,425
I have all the relevant information I need to use INFOR/ME2.	4,42	1,85	-,367	-,992
I have sufficient information to use INFOR/ME2.	4,50	1,82	-,417	-,940
I need more information to use INFOR/ME2.	4,51	1,81	-,425	-,608
<b>Perceived Usefulness</b>				
INFOR/ME2 improves my job performance.	4,79	1,52	-,884	,176
INFOR/ME2 increases my productivity.	4,40	1,60	-,529	-,474
INFOR/ME2 enhances my effectiveness on the job.	4,66	1,55	-,628	-,258
Using INFOR/ME2 makes it easier to do my job.	4,56	1,58	-,599	-,459
I find INFOR/ME2 useful in my job.	5,13	1,48	-1,04	,632
<b>Perceived Ease of Use</b>				
Learning to operate INFOR/ME2 was easy for me.	4,90	1,41	-,775	,156
I would find it easy to get INFOR/ME2 to do what I want it to do.	4,58	1,56	-,612	-,352
My interaction with INFOR/ME2 would be clear and understandable.	4,88	1,35	-,561	-,122
I would find INFOR/ME2 flexible to interact with.	4,18	1,64	-,216	-,890
It would be easy to use INFOR/ME2 correctly.	4,60	1,55	-,422	-,778
I would find INFOR/ME2 easy to use.	4,56	1,68	-,571	-,745

Note: Std. Error (Skewness = .18, Kurtosis = .36)

As explained in Section 5.2.2., the problem and failure code options depend on the class to which the equipment is configured. For the class, OTHER01, no options are available, except the OTHER-code. Therefore, the user cannot choose any other code than the OTHER code. To identify the level of consistency these cases of single-option-availability had to be filtered out. This is why the WO's that belong to the class OTHER01, were not taken into consideration for the consistency analysis. Therefore, the sample for the consistency part existed of 47373 WO's, 68% of the total sample set ( $N=69132$ ).

#### 5.4.2 Factor Analysis

To analyse item loadings per factor, a principle component factor analysis (PCA) was performed. Factor rotation was performed following the Direct Oblimin method, which allows for correlation between factors. In social sciences, behaviour is rarely uncorrelated and thus it is common practice to apply the oblique method (Hair et al. 2010). According to Hinkle, Wiersma and Jurs (2003) coefficients between (-)0.50 and (-)0.70 are moderately positive (negative) correlated, (-)0.70 to (-)0.90 highly positive (negative) correlated and (-)0.90 to (-)1.00 very highly positive (negative) correlated. Therefore, all item loadings higher than 0.50 were highlighted.

Table 3 shows that most items load on the variables as theorized in Chapter 2. The only exemption was item PA4: "I need more information to use [INFOR/ME2", which did not load onto any factor. After close investigation, the reason for this may be the fact that, PA4 was asked negatively, whereas the others inhabited a positive premise.

Cronbach Alpha computation without PA4 increased the reliability of the PA variable to  $\alpha = 0.83$  (vs.  $\alpha=0.54$ ). Therefore, in order to ensure a high statistical significance, PA4 was removed from further analysis. Although item PA4 was literally adopted from previous research of Venkatraman et al. (2006), it showed low internal consistency with the other PA items. Closer examination of PA4, concludes that the reason for this might be the negative premise of the question compared to the positive premise of the other questions.

#### 5.4.3 Correlation Matrix

Table 5 shows the bivariate correlations between Perceived Riskiness, Perceived Unambiguity, Perceived Usefulness, Perceived Ease-of-Use and an Overall Satisfaction. All variables correlated significantly with the Overall Satisfaction. Perceived Riskiness had a negative correlation with the other variables; the other variables were all positively correlated with each other on the individual level of analysis.

#### 5.4.4 Intraclass Correlation Coefficient

The unit of analysis of this research was the terminal. Therefore, the individual results needed to be aggregated to the terminal team level. To do so, this study followed the aggregation procedure from Homan et al. (2011) and Schippers et al. (2010) (results in Appendix G).

A one-way random ( $ICC1$ ) and a two-way random ( $ICC2$ ) intraclass correlation coefficient measurement, of the consistency type, were performed for the items in each of the variables. According to Dixon (2006) all variables PR ( $ICC1 = .80$ ,  $ICC2 = .80$ ), PA ( $ICC1 = .54$ ,  $ICC2 = .54$ ), PU ( $ICC1 = .93$ ,  $ICC2 = .94$ ) and PEoU ( $ICC1 = .91$ ,  $ICC2 = .92$ ) exhibited excellent average measures and are suitable for aggregation ( $ICC1 > .12$ ,  $ICC2 > .70$ ) (Dixon & Cunningham 2006). Therefore, the remainder of this chapter will explore the various TAM constructs at the aggregated terminal-level, which represents the team-level according to the results of the interviews.

TABLE 3: PRINCIPLE COMPONENT ANALYSIS

	RC 1	RC 2	RC 3	RC 4
PA1	.	.	.	0.86
PA2	.	.	.	0.84
PA3	.	.	.	0.84
PA4	0.41	-0.35	0.18	-0.26
PEoU1	.	0.81	.	.
PEoU2	.	0.74	.	.
PEoU3	.	0.70	.	.
PEoU4	.	0.67	.	.
PEoU5	.	0.81	.	.
PEoU6	.	0.79	.	.
PR1	.	.	0.58	.
PR2	.	.	0.60	.
PR3	.	.	0.83	.
PR4	.	.	0.81	.
PU1	0.76	.	.	.
PU2	0.83	.	.	.
PU3	0.83	.	.	.
PU4	0.81	.	.	.
PU5	0.78	.	.	.

TABLE 4: DESCRIPTIVE STATISTICS  
DSS ANALYSIS (N=69132)

Consistency	
<b>AMERICAS</b>	
a	25%
b	39%
c	40%
<b>ASIA</b>	
a	48%
b	47%
c	29%
d	66%
e	74%
f	32%
g	28%
h	46%
<b>EMEA</b>	
a	44%
b	50%
c	35%
d	53%
e	28%
f	29%
<b>NL</b>	
a	27%
b	58%
c	48%
d	33%
e	8%
f	55%

TABLE 5: CORRELATION MATRIX (N=143)

	1.	2.	3.	4.	5.
1. Riskiness	-				
2. Unambiguity	-.29***	-			
3. Usefulness	-.43***	.42***	-		
4. Ease of Use	-.37***	.54***	.64***	-	
5. Overall Satisfaction	-.51***	.48***	.59***	.66***	-

Note: \*\*\* Correlation is significant at the 0.001 level (2-tailed)

## 6 PHASE 3: REGRESSION ANALYSIS

In this last phase, the results from the pre-analysis in the second phase will be used to test the hypotheses. This chapter will first explain the procedure that was followed. Next, the regression results and the results of mediation examination will be presented.

### 6.1 PROCEDURE

Analysis was done on at the terminal-level (team-level) data set (N=23). The independent TAM variables, PR, PA, PU and PEOU, were first mean-centred to avoid multicollinearity, and cross-products for the traditional TAM variables (PU and PEOU) were computed (Aiken & West 1991). For the regression analysis the Lavaan software package was used in JASP (Rosseel 2012). JASP is a software package for statistical computation. Its main advantage is the user-friendly environment and interaction (JASP 2017). The Lavaan package uses Structural Equation Modelling (SEM) to examine regression and identifying moderating and mediating variables through path analysis (Rosseel 2012; Gunzler et al. 2013). To examine moderation effects between the TAM variables, SEM in the Lavaan package was used to conduct path analysis on the TAM part of the model. Next, SEM was used to perform a regression analysis on the data consistency. For both models fit-verifications were done by computing and testing GFI and Chi-squared tests and examining information losses with AIC/BIC. The Goodness-of-Fit Index explains how well a model fits the observations and is preferably larger than .90 (max 1.00) (Hair et al. 2010). The following paragraph presents the results of these procedures and the hypotheses tests.

### 6.2 HYPOTHESIS TESTING

#### 6.2.1 Technology Acceptance Model

**Overall Satisfaction** – SEM was used to perform a path analysis on the Overall Satisfaction of terminals (teams) with INFOR. Path analysis showed evidence for the moderating (indirect) effect (H1) of PEOU onto PU,  $\beta = .46, p < .001, CI [.58, 1.29]$ . Throughout this research a Confidence Interval of 95%, which is common in psychological research, was adopted (Cumming 2014). The results also supported H2,  $\beta = .46, p < .01, CI [.14, 1.04]$  and H3,  $\beta = .47, p < .01, CI [.14, 0.79]$ . For sake of clarity, each of these hypotheses is summarized in table 6. Therefore, the cross-product (PU\*PEoU) was computed and added as an additional direct effect on Overall Satisfaction in the model to determine the effects on data consistency.

TABLE 6: PARAMETER ESTIMATES (N=23)

Hypothesis	Regression	B	$\beta$	Std. Err	z	p	CI (lower)	CI (upper)
H1	PEoU ~ PU	0.93	0.73	0.18	5.11	<0.001	0.58	1.29
H2	PEoU ~ Overall Satisfaction	0.59	0.47	0.21	2.56	0.006	0.14	1.04
H3	PU ~ Overall Satisfaction	0.47	0.47	0.16	3.02	0.004	0.14	0.79

### 6.2.2 Data Consistency

**Data Consistency** – A regression analysis with SEM was conducted on the data consistency dimension. Fit statistics show that the new model, with the addition of the PU\*PEoU (indirect) effect, fits:  $GFI >.90$ ,  $\chi^2 = 16.19$  ( $p <.05$ ) (Table 7). Again, for sake of clarity, each of these hypotheses is summarized in table 7 and 8. The total variance explained by the model was  $R^2=0.32$ . A marginally significant negative relation between the Overall Satisfaction and Data Consistency was observed,  $\beta = -0.35$ ,  $p < 0.1$ ,  $CI[-12.96, 0.33]$ . This indicated that a decrease in Overall Satisfaction predicts an increase in Data Consistency. H4 thus had to be rejected. Regression analysis further showed a positive effect of PA on Consistency,  $\beta = 0.49$ ,  $p = 0.01$ ,  $CI[2.95, 20.89]$ . This indicates that an increase in PA causes higher Data Consistency. H5 thus was confirmed. The SEM regression analysis finally revealed a negative effect of PR on Consistency and thus supported H6,  $\beta = -0.47$ ,  $p < 0.01$ ,  $CI[-22.39, -3.41]$  (Table 8). This indicated that an increase in the Perception of Riskiness causes lower Consistency level of data.

TABLE 7: FIT STATISTICS (N=23)

	df	R <sup>2</sup>	AIC	BIC	GFI	$\chi^2$	p
Model	8	0.32	453.28	464.64	0.93	17.99	0.021

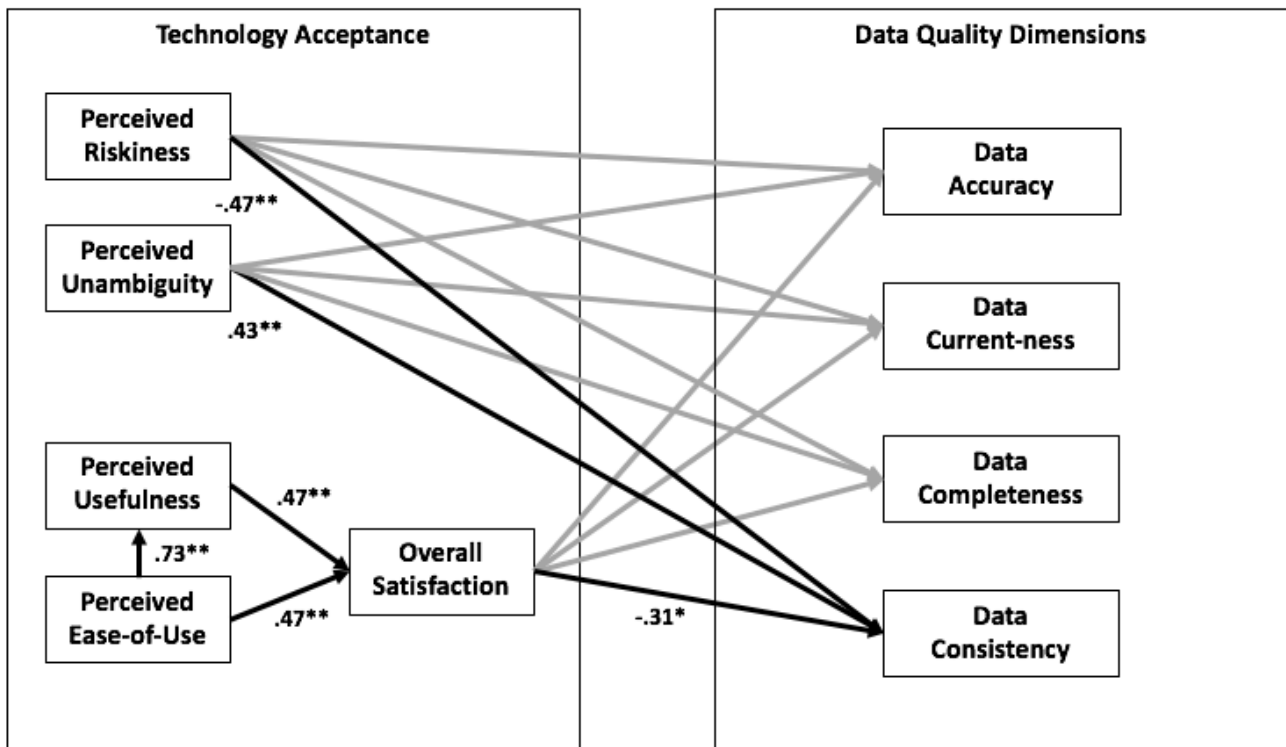
TABLE 8: PARAMETER ESTIMATES (N=23)

Hypothesis	Regression	B	$\beta$	Std. Err	z	P	CI (lower)	CI (upper)
H4	Overall Satisfaction ~ Consistency	-5.56	-0.31	3.43	-1.62	0.10	-12.41	1.29
H5	PA ~ Consistency	8.13	0.43	3.56	2.29	0.022	1.18	15.08
H6	PR ~ Consistency	-12.85	-0.47	4.82	-2.67	0.008	-22.61	-3.09

### 6.3 CONCLUSION

In this chapter, Structural Equation Modelling was used to conduct regression analysis. Support for the moderating effect of PEoU, H1, was found. Furthermore, analysis revealed evidence for the direct effect of PEoU (H2) and PU (H3) on the Overall Satisfaction. The SEM results revealed no significant effect of Overall Satisfaction on Consistency (H4). Lastly, regression results on the consistency model revealed support for H5 and H6, as Perceived Unambiguity (H5) was found to have a positive effect and Perceived Riskiness (H6) was having negative effect on Consistency (Figure 11). Next chapter will discuss these results and identify limitations, and it will also elaborate on scientific and practical relevance of this study.





Note: \* significant at the  $p=0.1$  level, \*\* significant at the  $p=0.05$  level

FIGURE 11: RESEARCH MODEL WITH REGRESSION RESULTS

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## 7 DISCUSSION

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### 7.1 SUMMARY OF FINDINGS

The aim of this research was to investigate the influence of team-technology satisfaction level on the data quality of Decision Support Systems. The study investigated a Decision Support Systems (DSS), called INFOR, and used literature from the field of Technology Acceptance Models (TAM) and Data Quality Management (DQM) to test variables in their predictive power regarding Data Integrity. The multimethod, comparative field study was performed at Royal Vopak, where the Data Integrity of the DSS under study, INFOR, was examined and correlated to TAM variables compared between terminals at the team-level.

### 7.2 SCIENTIFIC RELEVANCE

The biggest scientific contribution of this research is that the TAM methodology was applied in a business environment at the team-level measuring a real-life phenomenon. The inclusion of Perceived Riskiness and Unambiguity had significant effect and extended the TAM applicability to mandatory setting. The results of intraclass correlation tests approved aggregation of individual TAM results to team level, or in terms of this research: from employee to terminal level. At this level, TAM results were significant and similar to results observed in previous research on TAM at the individual level. Therefore, we can conclude TAM is applicable in team-technology collaboration research. This is a significant scientific result as it is the first-time in IS research, that TAM is used in combination with teams. This would increase TAM's usability in business settings even more, as modern businesses heavily rely upon the team-approach. Moreover this thesis observes the dependent variable or the actual phenomena objectively instead of a self-reported scale, which was one of the biggest limitations of TAM (Chuttur 2009).

More specifically on the present study, the results presented evidence for the positive effect of a team's Perception of Usefulness and Ease-of-Use regarding the DSS on the Overall Satisfaction the team gives to the DSS. This result was also expected by the managers who were interviewed and confirms previous TAM research (Venkatesh & Davis 2000; Davis 1986). Also, in correspondence with Venkatesh & Davis (2000) and Davis (1986), the moderating effect of perceived usefulness between perceived ease-of-use and the overall Satisfaction was supported by the results. In other words, all else held equal, a team that can interact with INFOR easily, needs less effort operating it, can allocate that effort to other activities, like focussing on the intended usefulness of the program, which contributes to the Overall Satisfaction the team experiences the DSS. This indirect, moderating effect is also observed in previous TAM research by Davis and Venkatesh (2000) and is consistent with the Theory of Planned Behaviour and Theory of Reasoned Action (Ajzen 1991; Madden et al. 1992). The results did also reveal significant relationships between Perceived Riskiness, Perceived Unambiguity and the level of Consistency in the dataset. Perceived Riskiness was found to have a negative effect on data Consistency. In other words, when teams perceive the prospected losses of using the program as high, the consistency of the data drops. Literature provides many examples of poor decision-making or wrong decision-taking in risky situations (Venkatraman et al. 2006; Yates 1992). Therefore, the verification of this hypothesis makes sense. Also, the support for the positive effect of Perceived Unambiguity on data consistency is backed by literature. In accordance with the results from Venkatraman et al. (2006), this study found evidence of the role of Perceived Unambiguity, which Venkatraman et al. call ambiguity, onto the willingness to accept the prospects of INFOR. In other words, the

higher the unambiguousness of INFOR is, the more consistent the data quality will be. No evidence was found for the positive effect of Overall Satisfaction on data Consistency. Although the Null-Hypothesis Significance Test (NHST) resulted in a marginally significant effect, the Confidence Interval (CI) ranged from -12.41 to 1.29 and thus crossed zero. When CI's cross zero it is common practice to observe the values within the range as negligible (Cumming 2014). Therefore, it can be concluded that the null hypothesis, in terms of NHST, is accepted. Moreover, it is interesting to observe that the effect size of Overall Satisfaction on Consistency is probably negative as most of the CI range consists of negative values.

Lastly, it has to be mentioned that this study focusses on collaboration components perception towards IT, willingness to work with IT and satisfaction with an IT system. In other words, this thesis observes the data quality issues from the social agent perspective. However, some researchers argue this is not a one-way problem. Orlikowski (1992) and Leonardi (2013), amongst others, have conducted extensive research into the relationship between humans and technology, to which they refer as the imbrication of social and material agencies. Their theory of Sociomateriality revolves around the belief that a certain technology affords users a certain set of applicability's (material agent) and that it is up to the user's perception how to interpret the ways of usage and what features are of interest for the task at hand (social agent; see Appendix H for an extensive examination of the concept). The imbrication of the material and social agents is restricted by affordances, rules and norms and will ultimately determine the usage, thus also usage quality, of the technology under study (Orlikowski 1992; Leonardi 2012; Niemimaa 2013). Practically the notion of Sociomateriality would trigger a deeper investigation into the way INFOR affords its users to choose non-OTHER codes, how are they listed, etc. However, application of the theory of Sociomateriality in practical context has not yet been done due to its abstract nature. The methodology of this thesis may stimulate operationalization of the material and social agents of the Sociomateriality theory.

## 7.3 PRACTICAL RELEVANCE

Practical implications of this research can be observed in two ways: As input for a Training and Team-Development Strategy and as method of gaining insight into global operations and deriving best practises.

### 7.3.1 Training and Team-Development Strategy

First, the results of this research can be used to develop a strategy to improve the human-generated data quality by developing training models for individuals and teams. Training and development, as part of the larger research stream focussing on organisational learning, is found to be a key ingredient for successful user satisfaction of IT (Gallivan et al. 2014). Training can reinforce the individuals' commitment to the organisation, it enhances flexibility and encourages the sharing of ideas and best practices, helping the transfer of knowledge, that is a key factor for operational advantage in global firms (Gómez et al. 2004; Carrillo 2004; Wang et al. 2015). Many studies of organisational learning investigate the correlation between training and performance on the individual level. However, Gallivan et al (2014) argue that IT usage is not merely an individual phenomenon, and thus IT training should be focussed on levels beyond the individual user. They claim that training is a relevant factor in shaping group attitudes and intentions to use IT. In other words, to improve IT acceptance and satisfaction, and thus IT usage behaviour, comprehensive team-level training should be given.

Tannenbaum and Yukl (1992) emphasize that designing a training module, should start with a training-need-analysis to establish who needs training, when it is needed and what should be taught. After

this pre-training analysis, the new training module should be designed (see directions for further research). The research performed in this thesis can be reviewed as such a pre-training analysis as it answers the questions of who, when and what. Following from the results it becomes clear what terminals should receive training (who) and in what order of priority: the terminals with lowest data quality should go first (when). With the results from the TAM survey can be established what training should be given at any specific terminal (what).

**Who** – From the results of current research, Vopak management can identify terminals that have a lower level of data consistency and thus are expected to have a lower level of data quality in general. This enables INFOR management to focus their effort and training on the weakest links. For example, the NL division has an average data consistency level ( $M=41\%$ ,  $SD=19\%$ ). The management should decide upon a data quality level limit that has to be achieved by every terminal. If management decides the limit to be 50%, being the first mile stone in the journey towards 95% data quality, they can observe that terminals 'a', 'c', 'd' and 'e' need to improve.

**When** – Of those four terminals that need training terminal 'e' performs the worst: Only 8% of the data from INFOR turned out to be consistent in terms of coding. Moreover, terminal 'e' has produced the most Work Orders in the last three years of all terminals included in this study. Therefore, the team from terminal 'e' would be selected to receive training first. In other words, in deciding who receives training first a balance between actual percentage of data quality and total amount of Work Orders has to be deliberated upon.

**What** – Compared to other terminals from the NL division, respondents from terminal e scored lower on perceived unambiguity, which may indicate that they did not feel they completely understand the program. As Perceived Unambiguity and Perceived Riskiness have the most powerful effect on data consistency, focused action can be undertaken to improve data Consistency. In terms of Unambiguity, a higher perception of Unambiguity means a higher perception of certainty while using INFOR. This would be improved by training teams in understanding the program. This does not necessarily have to focus on how it works, but rather on what is asked from them in every stage of the maintenance process. The feeling of certainty comes forth out of self-confidence, therefore training has to be aimed at stimulating self-confidence of understanding INFOR (Zikmund & Scott 1974). In terms of perceived riskiness, the results indicate that the perception of high risk reduces the consistency of data. Willingness to accept certain prospects, in this case the usage of INFOR, depends heavily on the perception of riskiness teams experience with INFOR. Although perceived riskiness levels are generally low for INFOR usage, it may benefit data integrity improvements for other IT applications. The interviewees pointed out that the feedback loop of monitoring and checking data input of predecessors, in reality does not take place due to the fact that separate maintenance roles are exhibited by the same persons. However, the knowledge that someone is checking your input may lower the perception of riskiness and therefore improve the data integrity per person and as a team.

### 7.3.2 Global Insight and Data Quality Awareness

The second practical implication of this research is that it gives Vopak an overview of their global data quality and that it creates awareness of the importance of data quality. Insights in terminal-specific levels of data quality across the world were not yet available. With this research Vopak has a holistic insight in a key part of their IT process quality and it can identify lagging terminals. Next to focussed training modules (paragraph 7.3.1) it is possible to identify best practices from the terminals that report high data quality levels. Lastly, the mere existence of this research creates awareness towards data quality. By periodically

repeating this research, Vopak not only can get a richer insight in the global performance of data quality, but it also stimulates the awareness throughout the workforce, that next to their capabilities to process and transport petrochemicals, their real key asset is the data they retrieve from this process. This would indirectly improve data quality of other DSS and IT systems.

## 7.4 LIMITATIONS

This section will examine the scientific and practical limitations of this research and it will suggest for possible solutions to improve this in case of reproduction. Limitations were found firstly in the statistical characteristics of this research design. Secondly, limitations involving the usage of a proxy in data quality assessment were experienced. Lastly, the applicability of TAM in mandatory and team-technology settings created some difficulties.

### 7.4.1 Statistical Power of Multilevel Models

There is growing attention to the vast body of underpowered studies in modern research (Maxwell 2004). Statistical power ( $\beta$ ) is the probability of correctly rejecting the null-hypotheses. Determining statistical power in multilevel models involves three main elements: effect size, sample size and desired level of confidence (Cumming 2014). Many studies lack the demonstration of statistical power to support the acceptance or rejection of the null-hypotheses (Hoenig & Heisey 2001; Maxwell 2004). Determining statistical power is an *ex ante* activity (Hoenig & Heisey 2001; Djimeu & Houndolo 2016; Scherbaum & Ferreter 2009). This research however, did not perform power computations initially. Instead, power computations were done afterwards and several limitations in relation to sample size were observed. This section, discusses the statistical power of this study and it elaborates on solutions to improve it.

In social sciences, research often encompasses *multiplicity*, that is the testing of multiple hypotheses. By examining multiple hypotheses error rates increase drastically and statistical power decreases (Maxwell 2004). In other words, by testing multiple hypothesis the probabilities of wrongly rejecting (Type I Error) and wrongly accepting (Type II Error) increase. Researchers often pay attention to avoid Type I Errors, and thus ensure statistical significance, but lack awareness for Type II Errors, which endangers the statistical power of their claims (Djimeu & Houndolo 2016; Hoenig & Heisey 2001; Scherbaum & Ferreter 2009). The remainder of this paragraph will investigate the elements of this research where Type I or II Errors could be made.

First, the measurement model tests in this research risk Type I Errors. As previously mentioned, the statistical significance ( $\alpha$ ), that is the probability of wrongly rejecting the null-hypothesis (Type I Error) is an important factor of statistical power ( $\beta$ ) as  $\alpha$  has an inverse relationship with  $\beta$  (Djimeu & Houndolo 2016; Scherbaum & Ferreter 2009). Usually, null-hypothesis significance testing (NHST), i.e. *p*-values, are of interest to ensure statistical significance, however there is a growing attention towards the pitfalls of NHST statistics (Goodman 2008; Cumming 2014). Cumming (2014) studied the power of NHST statistics and compared this to Confidence Interval (CI) statistics. He found evidence that CI's are generally better than NHST, and he argues that, as readers are found to interpret CI's better than *p*-values, it is scientifically beneficial to report only CI's (Cumming 2014). However, in this research results were reported by computing CI and *p*-values (Djimeu & Houndolo 2016; Cumming 2014). Therefore, future readers may focus on the *p*-values and risk wrongly interpreting the results. For example, this research reports the marginally significant correlation ( $p=0.1$ ) of Overall Satisfaction on Consistency, but also reports a CI[-12.41;1.29]. As the CI is very

small and crosses zero, the values are negligible and, in terms of the NHST world, the null hypothesis would be accepted. Thus, only observing the p-value would result in wrongly rejecting the null-hypothesis and thus committing a Type I Error. Yet, model fit and survey validity tests (Cronbach's Alpha, PCA, ICC) were only NHST tested, therefore this thesis risks wrongly interpreting their results and committing a Type I Error in the measurement model.

Secondly, the sample size at the aggregated team-level (Level-2) is very small and causes the whole thesis to risk underpowered statistical significance. To review the influence of this small sample size on the power of the study, a closer understanding of the ICC is necessary. The intraclass correlation shows the relationship between data provided by different individuals within a group (Scherbaum & Ferreter 2009). Strong group norms make it likely that group individuals perceive phenomena in similar fashion. Therefore, in multilevel models, large ICC values indicate that individuals within groups provide little unique information and thus only adding more groups, instead of more individuals per group, could increase the amount of unique information (Scherbaum & Ferreter 2009; Mathieu et al. 2009). In this research, ICC values were large compared to cut-off values mentioned by Dixon and Cunningham (2006). Therefore, a larger sample size at level 2, the team-level, does more to increase statistical power, than increasing the number of individuals within groups (Scherbaum & Ferreter 2009). Yet in this research, the level 1, the individual-level sample size was adequate (N=143, of total population=786 employees), whereas the sample size at team-level was small due to the small existing population (N=23 out of 39 terminals). Consequences of small sample size at the team-level are that error variations are less well explained and thus the probability that the observed effect is due to chance increases (Wolf et al. 2013). Small sample size also decreases the likelihood that a statistical significant finding actually reflects a true phenomenon (Button et al. 2013). Wolf et al. (2013) investigated sample size requirements for SEM and, although traditional rules-of-thumb mention minimum sample sizes of 100 to 200, they found evidence of minimum sample size of 30 cases (with four factors loading at 0.80). Therefore, it can be concluded that the level 2 sample size of N=23 in this research is not adequate and the results of SEM are statistically underpowered.

In order to increase the statistical power of this research, according to some researchers sample size has to be increased to >200 (Wolf et al. 2013). Yet, total population at Vopak entails only 39 teams. Luckily, advanced statistics literature offers a method to account for small sample sizes: The Bootstrapping Method. Although this thesis will not incorporate this method, it will be briefly introduced. But before that, it needs to be emphasized that, although this method helps to increase the statistical power of the analysis and results, it does not completely cure the disadvantages of small sample size research (Kirby & Gerlanc 2013).

Bootstrapping was developed by Efron in 1979. Bootstrapping relies on copying the original sample survey results, which is the best guess of representing the results of the whole population, a couple of times to approach the actual population, called the bootstrap population. Then it randomly resamples a new data sets over and over, that all will give results in the vicinity of the first 'best-guess' original sample survey results. If this is done, a normal distribution will emerge of results that deviate from the best guess result. By deciding upon a confidence interval, e.g. 95%, it is then possible to not make an educated guess, a guess of 95% certainty, between what values the best guess will be. Reporting the interval of the guess entails more statistical power and thus is statistically preferable (Rodgers & Rodgers 1999; Kirby & Gerlanc 2013). In a way, bootstrapping allows you to virtually create a larger sample size and thus increase statistical power, but it also decreases the preciseness of your result. The lower the original sample size, the broader the resample result distribution will be and the broader the resulting interval will be. Therefore, it is common practice to report the result interval and confidence interval as well as the best-guess result (Wood 2005).

#### 7.4.2 Data Quality Assessment

The study performed a data quality assessment, but investigated only one of the four data quality dimensions through a proxy. Literature provided measurement dimensions for assessing data quality in the form of reliability and integrity. To assess the data quality in INFOR, a proxy was chosen that reflected the data quality of the program. After examination of these dimensions, however, it became clear that the reliability variables, accurateness and current-ness, were not measurable in a non-longitudinal study. Therefore, only integrity variables were measured to indicate the data quality level. Sadly, the completeness variable proved to be of little use as results revealed no problems and thus no significant deviations in the data. In the end, data quality was assessed only on the basis of breaches of data integrity in the form of inconsistency. In summation, the dependent variable was theorized as explaining the data quality of a Decision Support System, but in the end, it was only measured through a proxy and only one out of four factors for data quality. Still, the proxy and consistency factor should explain data quality of human-generated data in the DSS, but they may not be really accurate.

#### 7.4.3 Applicability of TAM

Also on the topic of TAM, some other important limitations have to be mentioned: First, from analysis of the response in the clarification item at the end of each variable in the survey, it became clear that respondents may not have understood the questions of Perceived Riskiness very clearly. This may have impact on the face validity of the survey. Although PR items were found reliable and loaded very well on the same factor, this still might be due to chance. Second, limitation of this research is the fact that the study does not account for age, and cultural differences between respondents. Literature provides support that these factors have influence on technology acceptance (Kurkinen 2013; Straub et al. 1997). Moreover, respondents from the Americas and NL division use Spanish and Dutch, as their primary work language. However, the survey was in English and therefore may cause misunderstanding with some respondents less skilled in the English language. Third, it should also be mentioned that individual respondents were chosen out of a selection of terminals that used INFOR for at least three years. However, this does not mean that the individual respondents were using INFOR the same amount of time. Respondents might just have joined the terminal or company and therefore have far less experience with INFOR than others.

### 7.5 DIRECTIONS FOR FUTURE RESEARCH

The limitations of this research naturally provide for directions of future research. First, it is important to reproduce current research in a longitudinal setting, in which the data quality assessment should be performed more holistically. This means that the whole Total Data Quality Management cycle should be performed and all the data in INFOR should be included for analysis. Data quality of a DSS technology can only be measured of data that is regarded as significant. However, during the interviews it was observed that there was no consensus within Vopak of the data that is required and mandatory. This makes it hard to examine data quality, but more importantly it stimulates ambiguity. Users may not understand what fields are required and what are optional, therefore their level of perceived ambiguity decreases and eventually data quality drops. Therefore, the TDQM cycle will invoke several internal researches and projects at Vopak that should focus on guidelines of what specific data they need, what specifications every data point should have, etc. Another benefit of a longitudinal reproduction of this study is that cultural differences and their influences on technology satisfaction can be studied. Earlier TAM research proved that cultural differences



have significant effect on technology acceptance in voluntary environment, therefore there is an incentive to perform a similar study with the model from this research (Venkatesh & Davis 2000).

A second direction for future research is to redo the current study with a larger sample size, for example at a larger company like Shell or BP, to improve the statistical power and verify the results of this study. Especially in security and safety sensitive industries, like the oil and gas industry, poor data quality can come with disastrous consequences, as was illustrated with the *Challenger* case (Fisher & Kingma 2001). Moreover, the comparison of data quality levels and technology satisfaction between different firms may provide valuable insights for the industry. Yet, such a comparative study may be hard to conduct, due to privacy and competitive advantage issues.

Thirdly, a design study should be conducted in which the results of this study are translated into a training and development module. The module should be tailor-made to the specific needs of the underperforming terminals, but the development method should be universal in order to be used at different terminals and with different systems.

Fourthly, it would be very interesting to conduct a pre-test-post-test intervention research to investigate the effect of the training module on perception levels of TAM variables and data quality percentages. This would not only validate the results from this research, but it would also support TAM research in giving it practical relevance. Although some researchers used TAM for studying interventions, TAM results are usually used to gain insight in the psychology of potential users of a technology and therefore are exploratory in essence (Venkatesh & Bala 2008; Heckman et al. 2014). However, if the results from TAM would function as input for a training and development program, TAM would gain practical relevance.

## 7.6 CONCLUSION

In conclusion, this research investigated the influence team-technology satisfaction on the human generated data quality in the Decision Support System. This was done by studying the relation between the technology acceptance variables and data consistency in INFOR. A case study was performed at Royal Vopak, where the technology under investigation, the Decision Support System, INFOR, was analysed. Results provided evidence that data quality is positively influenced by perceived unambiguity and negatively by perceived riskiness. It also supported the direct and indirect effect of perceived usefulness in predicting the overall Satisfaction of INFOR users. Given the experimental combination of TAM and data quality assessment, it would be particularly relevant for future research to reproduce current research in a longitudinal setting at a larger case study company.

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## 9 APPENDICES

### A. VOPAK MAINTENANCE PROCESS, TASKS AND ROLES

Task	Responsible	Task description	Functionality INFOR
1. <b>Create PM or CM request</b>	Inspection or maintenance engineer	During an inspection, a failure is detected. The engineer or operator has to create a corrective maintenance (CM) request.	In this first stage INFOR affords the user to fill in 15 entries: description, equipment (object), department, critical safety, Organisation, type, class, status, priority, Cost code, problem code, requestors name, date, related WO and preliminary start date. Some of them are mandatory and all (except description) have a lookup table.
2. <b>Create WO</b>	Gatekeeper Maintenance	The gatekeeper reviews the request and adds additional information to create a work order.	In this second stage, INFOR affords the gatekeeper to add severity levels and failure, cause and action codes. Also, his name and date are asked. He also <i>estimates</i> the amount of hired labour, services, stock items, direct purchases and tool costs.
3. <b>Plan WO</b>	Maintenance Planner	The planner translates the WO into a planning of sequential steps of what to do when.	In the third stage, the planner <i>plans</i> the amount of hired labour, services, stock items, direct purchases and tool costs.
4. <b>Schedule WO</b>	Maintenance Scheduler	The scheduler plans the steps by the planner into the daily operations of the terminal.	In the fourth stage the scheduler sets the start date and planned closure date.
5. <b>Readiness and permits</b>	Maintenance Supervisor	The supervisor is the main check person after the gatekeeper. He is the last one to assess the WO and issue the work permits	No additional INFOR functionality is used.
6. <b>Execute WO</b>	Maintenance executor	Maintenance engineers perform the PM or CM following the guidelines of the WO.	No additional INFOR functionality is used.
7. <b>Validate WO results</b>	Maintenance Supervisor	Again, the supervisor checks if the WO is executed adequately and the equipment is up and running again.	In this seventh stage the supervisor needs to log date of technical completion of the WO.
8. <b>Book actuals</b>	Maintenance Planner	Next, the planner has to book the actual execution in relation to the planned steps.	In this eighth step the planner is able to enter the actual amounts of hired labour, services, stock items, direct purchases and tool costs. He also logs the actual closure date.
9. <b>Close WO</b>	Maintenance Manager	The maintenance manager is end responsible and he has to close the WO.	In the last stage, INFOR affords the manager to log administrative input, after which the job can be closed.

## B. INFOR INTERFACE

### Recordweergave

Beschrijving: \*  Organisatie: \*   
 Object: \*    
 Afdeling: \*   Procesveiligheid:

### Werkaanvraaggegevens

Type: \*  Aangevraagde  
 Klasse:   begindatum:   
 Status: \*  Probleemcode:   
 Werkprioriteit:   Kostencode:

### Oorsprong

Aanvrager:   
 Gemeld op: \*   
 Gerelateerde PM WO:

### Opmerkingen

[Opmerkingen toevoegen/wijzigen](#)

<p>Work Order: <input type="text"/></p> <p>Equipment: * <input type="text"/> <input type="text"/></p> <p>End Position Selected: <input type="checkbox"/></p> <p>Department: * <input type="text"/></p> <p>Location: <input type="text"/> <input type="text"/></p> <p>Type: * <input type="text"/></p> <p>Class: <input type="text"/> <input type="text"/></p> <p>Status: * <input type="text"/></p> <p>Priority: * <input type="text"/></p> <p>Highest Criticality: <input type="text"/></p> <p>Warranty: <input type="checkbox"/></p> <p>Safety Severity: <input type="text"/> <input type="text"/></p> <p>Environmental Severity: <input type="text"/> <input type="text"/></p> <p>Operational Severity: <input type="text"/> <input type="text"/></p> <p>Customer Severity: <input type="text"/> <input type="text"/></p>	<p>Required Completion</p> <p>Date: <input type="text"/></p> <p>Cost Code: <input type="text"/> <input type="text"/></p> <p>Problem Code: <input type="text"/> <input type="text"/></p> <p>Critical: <input type="checkbox"/></p> <p>Safety critical equip.: <input type="checkbox"/></p>	<p>Organization: * <input type="text"/></p> <p>Terminals: <input type="text"/> <input type="text"/></p> <p>Parent CM Work Order: <input type="text"/></p> <p>Asset: <input type="text"/></p> <p>Created By: <input type="text"/></p> <p>Date Created: <input type="text"/></p> <p>Parent Work Order: <input type="text"/></p> <p>Related PM WO: <input type="text"/></p> <p>Budget Approve * Required: <input type="text"/></p> <p>Budget Approved by: <input type="text"/></p> <p>Operation Witness Req?: * <input type="text"/></p> <p>Witnessed by: <input type="text"/></p> <p>MOC Required?: * <input type="text"/></p> <p>MOC Reference: <input type="text"/></p>
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### Extra Definition Fields

WO Supervisor:

Planner:

Scheduler:

Reason for Rejection:

Reimbursable Costs:

Reason for Reimbursable Costs:

### Scheduling

Reported By:

Date Reported:

Earliest Starting Date:

Duration:

Actuals Start Date:

Actuals Date Completed:

### Work Order Details

Standard WO:   Route:

PM Code:   Action Code:

Original PM Due Date:   Failure Code:

Reason for PM:   Cause Code:

Downtime Hours:

Downtime Cost:

### Custom Fields

### Activity

Activity:

Trade:   Estimated Hours:

Task:   Hours Remaining:

Material List:   People Required:

## C. VOPAK TERMINALS

Division	Terminal	Terminal abbreviation	Within sample?
NL	Chemiehaven	VCLC	Included
NL	TTR	VCLT	Included
NL	Vlaardingen	VCVL	Included
NL	Botlek	VCLB	Included
NL	Westpoort	VTNW	Included
NL	Europoort	VTRE/VTEP	Included
EMEA	Fujairah	VHFL	Included
EMEA	Leftbank	VTLE	Included
EMEA	Eurotank	VTEU	Included
EMEA	ACS	VTAC	Included
EMEA	Algeciras	VTAG	Included
EMEA	Durban	VTDU	Included
AMERICAS	Los Angeles	VTWA	Included
AMERICAS	Deer Park	VTDP	Included
AMERICAS	Vopak Terminal Venezuela	VTVE	Included
ASIA	Vopak Terminals Singapore (Sebarok)	VTSG	Included
ASIA	Vopak Terminals Banyan	VTBA	Included
ASIA	Vopak Terminal Jakarta	VTJA	Included
ASIA	Thailand TTT	VTTH	Included
ASIA	Vopak Terminal Merak	VTME	Included
ASIA	Australia Sydney B	VTSY	Included
ASIA	Vopak Terminal Darwin	VTDA	Included
ASIA	Vopak Terminals Sakra	VTSA	Included
NL	Laurens haven	VTLH	Not included
NL	Eemshaven	VTNE	Not Included
NL	Vlissingen	VCVS	Not included
NL	HQ	VLNL	Not included
AMERICAS	Long Beach	VTWB	Not Included
AMERICAS	Brasil - Alemoa	VTAL	Not included
AMERICAS	Brasil – Aratu	VTAT	Not included
AMERICAS	Mexico - Altimira	VTAM	Not Included
AMERICAS	Mexico - Coatzacoalcos	VTCO	Not included
AMERICAS	Mexico - Veracruz	VTVC	Not Included
ASIA	Vopak Terminal Banyan Rock Caverns	VTBC	Not included
ASIA	Vopak Terminal Penjuru	VTPJ	Not included
ASIA	Vietnam	VTVN	Not included
CHINA	Vopak Sealink Terminal Dongguan Co. Ltd.	VTDO	Not included
CHINA	Vopak Shanghai - Caojing Terminal	VTSH	Not included
CHINA	Vopak Terminal Zhangjiagang	VTZH	Not included

## D. INTERVIEW: INFOR APPLICATION MANAGER

### Maintenance process

The INFOR application manager is continuously involved with fitting INFOR to the needs of the terminals, troubleshooting issues and developing new applications and additions to improve INFOR and the maintenance process. The tasks in the maintenance process are logged in INFOR. Operators detect issues and log their findings in INFOR. Supervisors review the work orders and maintenance managers put it through to the technical service who fix the problem. A software support application is crucial for these day-to-day overviews of the corrective and preventive maintenance. However, it is the application manager's responsibility and vision that data is used for solving the issues of the day after tomorrow, issues that may not yet have emerged. To do this analysis of raw structured data has to be performed.

### INFOR experience

INFOR is the enterprise asset management (EAM) program that Vopak uses to manage the maintenance process. Its main purpose is to afford users the possibility to store, analyse and visualise maintenance records. The application manager praises INFOR for its flexibility, user-friendliness and broad applicability. INFOR is used at the 39 Vopak terminals divided amongst the five divisions. The first terminal started working with INFOR in 2008. In those early years, focus was on the global roll-out and implementation of the program. Every terminal was appointed a key user who was trained in using INFOR. Next in line, the divisional key users, transferred the complaints and issues from the terminals to the global key users at the Headquarters. Over the last 10 years almost every terminal started to use INFOR and a rich collection of work orders was gathered. Every terminal is responsible for their own configuration and correct usage. After analysis, it seems that the quality of the data in the collection differs a lot per terminal. One of the cases in which this is best observable is the coding of problem, failure, cause and action factors.

For every Work Order collected there has to be filled in four standardized codes that explain the nature of the problem, failure reason, identified cause and actions taken. These codes are used for analysis to determine what the most frequent problems, failures and causes per equipment are and what actions are mostly performed to solve them. The options for problem and failure codes are dependent to the class of the equipment. Therefore, every piece of (new) equipment used at the terminal has to be correctly configured to a class. Cause and action codes are general and not linked to anything. They have to be configured just once. Errors or inconsistencies can be observed either in the actual selection (documentation) of a code or the initial configuration of the codes.

The use of these codes in terms of ad-hoc documentation and configuration is very inconsistent. It is noticed that the OTHER code is selected for all four factors in most of the work orders. As only 10% to 15% would be logically explainable, 70% of OTHER codes is not. This is a sign of inconsistency and incorrect documentation of configuration.

Moreover, the global key user experiences missing entries. Only a few entries are mandatory, but most are voluntary and case specific. Next to missing codes, this is also observable in the severity levels that have to be configured to every equipment once it is acquired. Every new piece of equipment has to be configured in a certain class and it is rated on operational, customer, environmental and safety severity once it would fail. However, it is noticed that a lot of terminals do not do this. Lastly, the application manager observes missing entries in the task description. Within every corrective work order it is possible to create a task to solve the issue. For this task a description, estimated hours needed and estimated employees needed is asked. However, it is experienced that a lot of tasks lack an entry for these last two aspects.

In other words, the application manager is fairly positive about the program, but observes several problems with the usage of the program in the field.

#### **Perception of INFOR experience of others**

The application manager assumes multiple reasons for the inconsistency experienced. First of all, she questions the user perception regarding usefulness and significance of the program. Secondly, she mentions the possibility of insufficient program-knowledge and support. Thirdly, she acknowledges the possibility for complaints about the usability of the program, however, she does not experience this directly herself.

## E. INTERVIEW: INFOR GLOBAL KEY USER

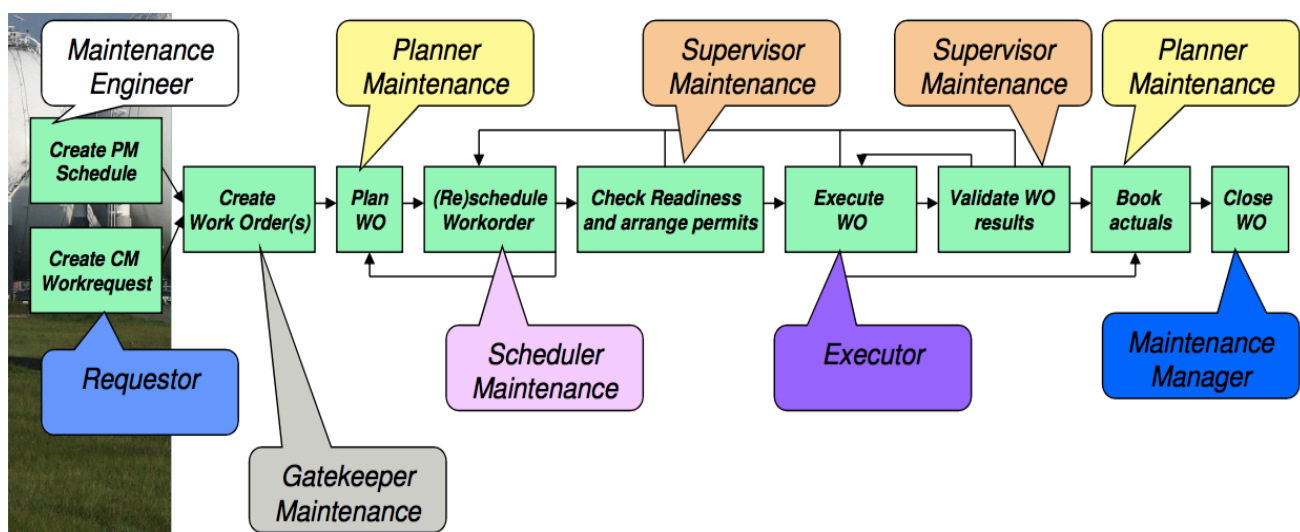
### Maintenance process

The global key user is responsible for collecting problems and issues of the divisional key users and provide support to solve them. He is in close contact with the application manager and program supplier to adjust the software if needed. Back in 2008 INFOR was acquired and configured to match the blueprint of the maintenance process. He emphasizes that INFOR is specifically adjusted to the maintenance process and not vice versa. Therefore, he argues that if the maintenance process is slow, this is not due to the fact that the program is slow, but because of inefficiencies in the blueprint.

In the first stage the requestor (or engineer) detects a malfunction and starts a work request. Back at the computer in the office he creates a work order and fills in the description, equipment (object), department, Organisation, type, priority, problem code, requestors name, date and comments. Next, the gatekeeper reviews the work order and decides if the request is valid and what the priority for action is supposed to be. After this, the planner, scheduler and maintenance supervisor prepare the maintenance works. In all these steps input in the form of cost estimations, presupposed duration and starting dates, workforce estimations, replacement part purchase etc., has to be entered into INFOR. Then, after execution, technical and administrative documentation has to be done. Technical documentation contains carefully selecting the right problem, failure, cause and action codes. Administrative documentation consists of correctly logging the duration, costs, responsible employees, etc. After this administrative documentation, the maintenance cycle is completed and the WO is officially closed.

### INFOR experience

INFOR offers the user 82 entry possibilities of which most are lookup tables. Only the requestor has mandatory fields to fill in, after which it is up to the user to fill in something or not. Every task has a task-owner. Every task owner has the possibility to enter additional information and check already logged information. Therefore, after one maintenance cycle from creation of request to the closing of the WO, the required fields have to be filled in and checked numerous times by different people. In reality however, it appears that different task-roles are owned by the same person. His personal experience with INFOR is positive. He specifically mentions the fact that INFOR is very flexible to adjust for user requirements. He also states that INFOR is clear, understandable and fast-working.



### **Perception of INFOR experience of others**

As global key user, most of the complaints, issues and rumours about the program come to his attention. He thinks that the most important reason for lacking data quality, is that employees not acknowledge or see the added value of taking the time to fill in the work orders adequately. Indirectly this could be caused by the fact that it takes too much time to correctly make and process a work order. Yet this would be caused by the blueprint instead of the program. He also mentions the fact that follow-up training is needed. Within these 10 years, new people started working with INFOR and he thinks the direct knowledge about the capabilities, usefulness and possibilities of INFOR is missing.

## F. INTERVIEW: MAINTENANCE ENGINEER TECHNICAL NL, DIVISIONAL KEY-USER

### **Short summary of the Maintenance process**

The corrective maintenance process at Vopak observed from a technical perspective is carried out by two entities: operations (OPS) and technical services (TD). In short, an operator (OPS) detects an asset failure and requests a work order (WO). Important at this stage is the description of the failure and problem. In the future, the possibility of adding a picture could prove very valuable. The requested WO is then reviewed by a supervisor called the gatekeeper (OPS). The gatekeeper needs to review the information offered by the operator and in case of insufficient information he has to send back the WO to the operator. However, in reality this never happened and the gatekeeper fills in the required entry fields himself or leaves them blank. After the WO is approved TD starts by preparing the necessary work plans. In this first stage, it is very important that problem, codes is logged correctly. Moreover, TD has to review the data that is already entered and improve where necessary. When the work is finished, the supervisor (TD) will perform administrative tasks and closes the WO and add the failure, cause and action code before the WO can be closed.

### **Manager's INFOR experience**

The manager's opinion regarding INFOR is moderately positive. He sees the usability and potential of the program, if it would be used correctly. However, he experiences some quality problems with the WO's: In his opinion there is little to no feedback by the gatekeeper on the data quality provided by the operator. He also emphasizes the complexity of the object-structure within INFOR. The object-structure is the breakdown structure in which all equipment are 'logically' represented. This should support fast selection of end-equipment and analysis. Yet, the structure is not as logical as it could be, which makes it harder for the operator to find and select the right equipment end-position. Moreover, he mentions that some terminals lack the right configuration of their equipment with respect to severity, class and criticality.

### **Manager's perception of INFOR experience of users**

The interviewee emphasizes two main concerns regarding the user-experience of INFOR: First of all, he mentions the lack of awareness with OPS and TD regarding the importance of (data) quality. This is enforced by the fact that incorrect usage and thus low quality, has no sensible on-the-job impact for the operation. Secondly, the interviewee thinks that INFOR end-users lack the proper information and knowledge about the possibilities of INFOR. This might be due to absence of training and support.



## G. AGGREGATED TAM RESULTS PER TERMINAL

TABLE 9: AGGREGATED TAM RESULTS PER TERMINAL

	Perceived Riskiness		Perceived Unambiguity		Perceived Usefulness		Perceived Ease of Use		Overall Satisfaction	
	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation
<b>AMERICAS</b>										
a	2.39	1.39	4.50	1.16	4.55	1.59	4.76	1.66	6.53	2.32
b	1.50	0.71	3.00	2.47	4.70	2.40	4.25	1.77	6.00	1.41
c	2.33	1.15	4.58	0.58	5.20	0.40	4.00	1.01	6.00	1.00
<b>ASIA</b>										
a	2.50	0.71	4.88	1.24	4.80	0.00	5.33	0.94	6.50	2.12
b	2.00	0.00	3.75	0.35	5.20	1.41	4.00	1.65	5.50	2.12
c	2.85	1.22	4.80	2.25	6.12	0.86	6.13	0.83	7.60	0.89
d	2.00	1.41	5.88	1.24	6.20	0.28	5.75	1.77	7.50	0.71
e	2.44	1.21	4.88	0.72	4.60	0.85	4.88	0.90	6.00	1.15
f	2.75	1.41	3.88	0.18	3.80	2.55	4.08	0.12	4.50	0.71
g	2.50	1.02	3.31	0.24	2.55	0.85	3.54	0.55	4.25	2.06
h	1.38	0.53	4.38	3.01	6.40	0.85	5.83	0.94	7.00	1.41
<b>EMEA</b>										
a	1.82	1.06	5.32	0.88	5.18	1.79	5.38	1.32	7.09	2.12
b	2.93	1.22	4.13	0.81	4.70	1.50	4.17	1.27	5.30	1.64
c	3.11	1.11	4.98	0.95	5.18	0.65	4.59	1.12	6.18	1.54
d	2.17	1.04	4.92	2.01	4.67	2.21	5.28	1.75	6.00	1.73
e	3.75	0.85	4.64	0.86	3.56	0.90	4.31	0.82	4.44	1.42
f	2.65	1.46	4.70	0.67	4.40	0.73	4.33	0.91	6.20	0.84
<b>NL</b>										
a	2.73	1.30	4.63	1.04	4.56	1.55	4.44	1.26	5.86	1.99
b	1.56	0.43	4.94	0.94	4.35	1.18	3.96	0.89	5.75	1.71
c	2.75	1.32	4.94	0.66	3.95	0.96	3.96	1.21	6.00	0.82
d	3.21	1.16	4.43	0.66	3.80	2.00	4.31	1.30	5.71	1.89
e	2.41	0.86	4.41	1.08	4.59	1.26	4.38	1.23	6.94	1.18
f	2.88	0.88	3.75	0.35	5.50	0.14	4.42	1.53	6.00	1.41

## H. STRUCTURATION THEORY AND ACTOR-NETWORK THEORY

To examine the theory of Sociomateriality it is necessary to identify prior theories attempting to explain the same or similar phenomenon. In the case of Sociomateriality, Antony Giddens theory of Structuration (1984) was of great influence. His theory was based on the belief that complex social systems could be easily described by a combination of *structure* and *agencies*. Giddens believes that social interactions in such systems are coming forth out of the capacity of the individuals within the system to exhibit a certain social activity, hence the power to exert a certain behaviour or action. He calls this the *agency*. To describe social systems across a spectrum of time and space, or in other words history, he adds the element of *structure* that consists of rules and resources that exist across time and space and therefore 'binds' the time-space in social systems. However, Giddens acknowledges the reciprocal nature of these rules and resources as *structure* is also a result of the social practices that exist. He calls this the *duality of structure* (Giddens 1984). Although theoretically interesting, Giddens received some criticism on his theory.

One of the major limitations of Giddens' work, in light of IS research, is the fact that the theory is highly abstract and therefore it is lacking in offering methodological guidelines, especially in the case of incorporating the material world of technological artefacts (Walsham 1997 p.468). In order to resolve this criticism, Bruno Latour (1987) proposes the Actor-Network Theory (ANT). ANT is concerning the behaviour in the form of motivations and actions of groups of linked actors. The novelty of this theory is that actors include human and non-human actors, such as technological artefacts. The linkages between those groups of actors form a heterogeneous network of aligned interest and associations (Walsham 1997 p. 469). Although ANT incorporates the non-human entities and acknowledges their position in the social system, it fails in analysing the bigger social structure as it merely addresses the local and contingent (Walsham 1997 p. 472).

Wanda Orlikowski acknowledged the larger *social-system of rules* and *structure-agency* distinction of Giddens. She also supports the incorporation of the non-human actor inclusion, but she argued that social interactions through, or with, the non-human actor, i.e. the technology, are strongly depended on the availability of actions exerted by the technology. In other words, the capacity of actions afforded by the technology (Orlikowski 2000; Orlikowski 1992). This description of a technology's *power*, should be incorporated in the non-human actor description. Orlikowski's work combined the work of Giddens and Latour and introduced the terms *social agency*, the *power* of human actors, and *material agency* to explain the *power* of the non-human actors. Together with this perspective, the term Materiality was introduced to explain the material entity. However, the exact definition of materiality created confusion and discussion (Leonardi 2012).

### i. Materiality

First of all, the word, materiality, could logically be related to physicality. So, the materiality of physical objects or tools is easily described. However, in the light of IS research, digital objects or tools should also have a materiality. The material of such an object is far more difficult to describe because of its intangibility, but it is definitely material and therefore incorporated in the definition of materiality. Yet, material is not the only important element of materiality. Kallinikos (2004) proposed the addition of the form in which a material is ordered (Kallinikos 2004). Adding this element to the definition would result in a combination of material and form that is called materiality. In this definition, the material and form would be independent

from time and place, which makes the term materiality useful, as it is inherently available in the same way to all its users (Leonardi 2012). An important note has to be made about the timeless feature of materiality: In time the same technology changes (by means of updates or versions) and therefore materiality changes. To claim that materiality is timeless, the time-scale of defining timeless should be scoped to the level of which the materiality stabilizes in its evolution (Leonardi 2012; Leonardi 2013; Orlikowski 2000). Lastly, it should be observed that material and form only are important if they matter to a user (Leonardi 2010; Leonardi 2012). Taking these three elements into account, Leonardi (2012) gives a clear definition of the abstract materiality concept:

*“Materiality is the arrangement of an artefact’s physical and/or digital materials into particular forms that endure across differences in place and time and are important to users (Leonardi 2012, p.10).”*

However, the notion of Materiality in itself does not nearly explain technology usage as a whole. Therefore, a lot of research is conducted towards the existence of technologies in social systems. This is when new notions like, technology-in-use and socio-technological ensembles, arose (Orlikowski et al. 1995). In essence these perspectives suggested that technologies themselves matter very little. What matters is the way people use them (Leonardi 2010; Leonardi 2012). In other words: a social element is needed.

## ii. The Social Element

The social part of the term Sociomateriality puts focus on the creation and usage of materiality. In other words: how potential users shape the development of the materiality and how they eventually use it regardless of what the materiality’s intention is. As explained in the first section of this chapter, the theory of Sociomateriality logically follows the work of Giddens (1984) and Latour (1987). Orlikowski (2000) adapts Giddens’ perspective on social systems and the social capacity to form goals and objectives and she incorporates Latour’s distinction in human and non-human actors. Following from this a social element, with a certain social agency emerges that is completely independent, yet logically linked to, all non-human actors and is part of a bigger social structure.

*The social element represents the human capacity to make goals and activate, a certain technology’s material and form, independently from the materiality’s intention, in order to realize one’s goals (Giddens 1984; Orlikowski 2000; Walsham 1997).*

## iii. Imbrication or Constitutive Entanglement

It becomes clear that Sociomateriality is not the same as technology, but instead it is the ‘practice’ of technology in interaction with a social entity (Leonardi 2013). This ‘practice’ is more specifically described as the ‘space’ in which the social and the material become intertwined. At this level, the theory of Sociomateriality knows two streams: one that observes the world from a critical realism perspective and one that embraces an agential realism perspective. The two perspective mostly differ in their ontological world-view, or according to *Merriam Webster Dictionaries*: The perspective of what entities have existence and how they can be grouped according to their similarities or differences. In essence, critical realism

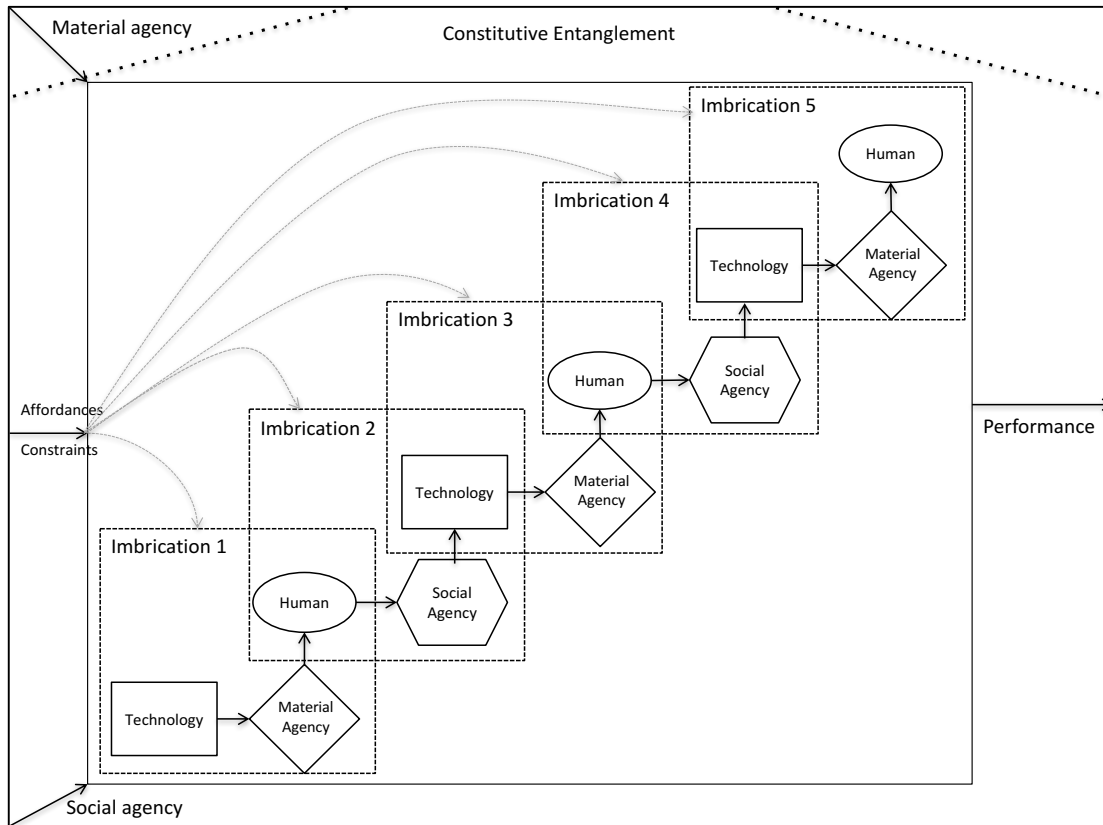


FIGURE 12: RECIPROCAL IMBRICATION IN CONSTITUTIVE ENTANGLEMENT, A COMBINED CRITICAL/AGENTIAL REALISM PERSPECTIVE.

presupposes that the world is ontologically stratified, which results in observing the social and material domains as separated and discreet entities on different levels. Agential realism, on the other hand, presupposes the world is ontologically relational and thus the material and social agencies on the same level and are only distinct in their mutual relationships (Niemimaa 2013 p.6). Therefore, realists focus on the relationship rather than on the entity. These two, different world-views mostly affect the definitions of elements within the theory of Sociomateriality: critical realism defines the space of agential intertwinement as imbrications of the independent material and social domains. On the other hand, the agential realists mention a space of constitutive entanglement as the material does not exist without the social and vice versa. This thesis will not dive further into the classification of both realisms, but it will adopt a middle-ground in which both perspectives are combined (figure 12). This means that the process of technology usage and development follows an imbrication process, and will be denoted with the verb ‘to imbricate’, in a space where the inherent socio-material and material agents constitutively entangle (Bratteteig & Verne 2012). Yet in this view, there exist a contradiction, because materiality exists independent of humans, but affordances, and constraints, do not. Therefore, the material agent exhibits a certain possibility of usage and

it depends on the perceived affordances and constrains, if they are used. In this view, affordances and constraints are constructed in the space between social and material agencies as a layer through which the social and material agencies imbricate.

As has been stated before: creation of materiality is a social endeavour, but social interaction often exists because of materiality. Therefore, the theory of Sociomateriality argues that the social and the material part of technology are inherently reciprocal and therefore cannot be studied separately. This last statement finalises the creation of a holistic and unambiguous definition of Sociomateriality that will be used in the proposed research:

*Sociomateriality is the practice of a technology in a space where social and material agencies imbricate reciprocally in constitutive entanglement, submissive to affordances and constraints exerted by those respective agencies, to give function and character to the particular technology.*

The application of Sociomateriality as a method for guidance in organisational and IS research has grown steadily since its birth (Lim & Mingos 2015; Orlikowski 2007; Orlikowski et al. 1995; Orlikowski & Scott 2008). However, research focuses itself mainly on the level of the organisation and its employees as one unit. It might be interesting to change the unit of analysis towards organisational departments and their management to see whether integration of them can be explained and improved from a sociomaterial perspective.