

MASTER

Improving the manageability of online product detail page elements design of a software tool to facilitate mass product monitoring

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Improving the manageability of online product detail page elements: design of a software tool to facilitate mass product monitoring.

Master's Thesis

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in partial fulfilment of the requirements for the degree of

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Executive Summary

Introduction

The digital transformation has enabled new possibilities of transactions and processes. With the increasing success of new digital business models, the attention is growing in marketing and organizational research regarding the factors that caused success in e-commerce. Different factors, identified in literature, influence the sales velocity of a product at an online retailer (e.g. Amazon, bol.com, Coolblue) and therefore the success of a product. Most of these factors are found on a product detail page (PDP). A PDP is a web page on an online retailers' website that provides information on a specific product. On these pages different PDP elements are present. The PDP elements together determine the quality of the content of the PDP. According to recent market studies, product information on retailers' site is very important for the consumers during the buying process. For this reason, the importance for the retailer and the manufacturing company to optimize the elements that determine the content quality on the PDPs to increase sales and stay competitive. Monitoring and managing the content quality at different online retailers, from the viewpoint of the seller, could be very valuable to increase the conversion rate and sales velocity of product. Missing product images or videos, no product reviews, incorrect product titles and product descriptions are some of the examples that lead to insufficient content quality of the PDP. The cause of insufficient content quality of a PDP, in most cases, is due to incorrect or incomplete information upload by sales and marketing employees to online retailers or by employees of the online retailer itself. Furthermore, retailers like Amazon and Bol.com, that allow independent third-party sellers to sell their products via their channel, are also giving the ability to these sellers to change product information on PDPs. The current problem Signify is facing is that, for their PDPs with insufficient content quality, they are not able to monitor and manage these PDPs in a sustainable and workable way. To monitor, manage and improve the content quality of the PDP, currently a salesperson must check a PDP manually to see if the content quality is sufficient and would report the insufficiencies manually

For this research, the objective is to design a software tool that sales- and marketing people can use to monitor and manage the PDP content quality across multiple online retailers in the Netherlands and Belgium. Monitoring and managing these product page elements to optimize the PDP's content quality contributes to increasing the conversion rate. Subsequently, the following research question is answered: *"How can a software tool be designed to facilitate mass monitoring of online product detail page elements to manage the product page content quality and therefore improve the conversion rate?"*

Furthermore, to help solve the main research question, five sub-research questions have been formulated:

1. *What is the current way of managing content at PDPs?*
 - *1.1. How are PDP elements currently managed?*
 - *1.2. Which PDP elements can be directly managed upon by Signify?*
2. *Which PDP elements are determinants of the PDP content quality affecting conversion rate and sales velocity?*
3. *Which data dimensions are relevant for the data quality of the tool?*
4. *How can PDP content quality be assessed?*
5. *How can the tool interface be designed?*

Research methodology

The research design is based on design science research initiated by Simon (1996). The aim of the design science research approach is to develop knowledge to design interventions to solve business problems and to design innovative artifacts to solve construction problems. To structure of the design science approach, the problem-solving cycle from Van Aken et al. (2007) is applied. The problem-solving cycle tries to develop scientific knowledge in aid of creating design propositions that establishes guidelines for developing the final solution. Since the problem-solving cycle is a fairly general design approach for a wide range of business problems, an additional research process model by Moultrie et al. (2007) is used to make the research design more specific for this study since this model was used for the design of a software tool. This research process consists of three phases: the exploratory study, tool development & testing and validation. Both models are combined in the final research design.

The goal of this research is to design a tool, based on scientific and practical knowledge, that is used for monitoring the online content quality of PDPs. To facilitate that goal, a theoretical analysis and empirical research was done. The theoretical analysis discusses the research from literature and aims to get an understanding of the current scientific- and practical knowledge regarding online content management and tool design. Knowledge on the conversion rate and its antecedents, data-driven support systems, data quality and dashboard design were gathered and elaborated. The outcomes of the theoretical analysis were used during qualitative empirical research with company experts and for the determination of the design requirements of the tool. After developing the initial design of the monitoring tool, based on the design requirements, the initial design was tested and validated through user testing on different criteria. In the last part of the research design, the final tool design is presented after improving the initial design based on the outcomes of the testing and validation.

Analysis & Diagnosis

The outcomes of the expert interviews, as part of the qualitative empirical research approach, are analyzed in the expert data analysis. Following the outcomes of the expert analysis, the sub-research questions were answered. Based on these outcomes, together with the outcomes of the theoretical analysis, 13 design requirements were identified that serve as input for the solution design of the monitoring tool. These design requirements consist out of the functional requirements, user requirements, boundary conditions and design restrictions.

Solution Design

Through an iterative design process, the monitoring tool has been designed. The design requirements for the tool served as input for the initial design of the tool. After the elaboration and explanation of the tool and the underlying principles, the initial design was tested and evaluated on three criteria and the design requirements in order to present the final solution design. The final solution design consists out of a Microsoft Excel based tool that uses external scraping data from PDPs and internal data to make assess the online content quality. The data is presented through two dashboards and 17 drill-down tabs that gives the user of the tool insights about the online content quality at different retailers. In Figure 1, the retailer dashboard is shown from where the user can monitor and manage the content quality and other elements that are present on a PDP.

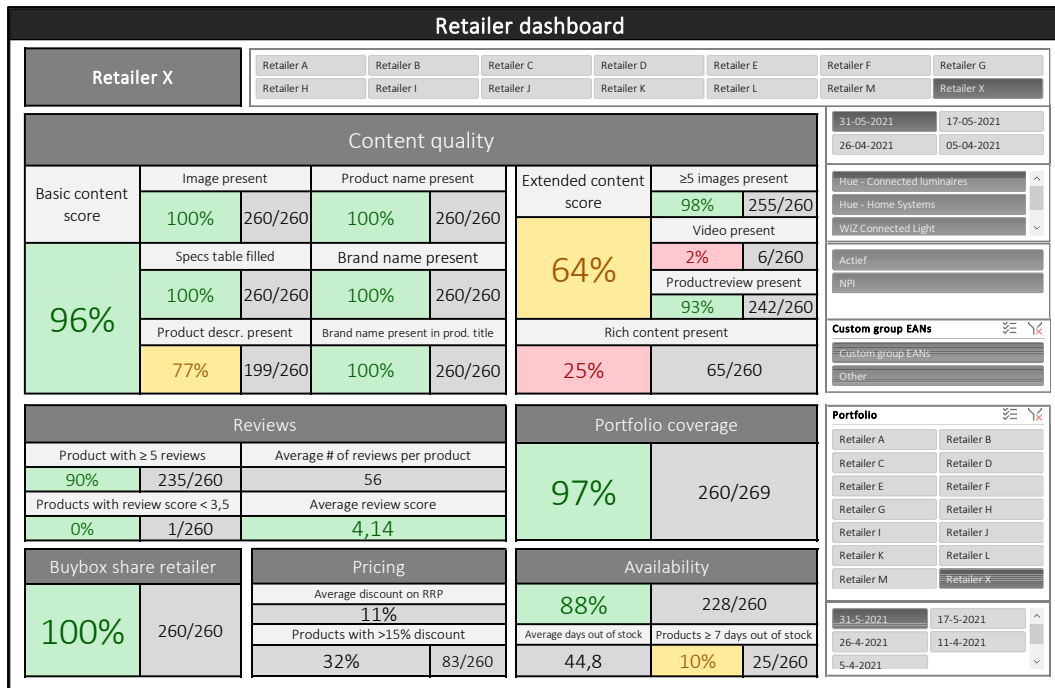


Figure 1 - Retailer dashboard from monitoring tool

Conclusion

The goal of this research was to improve the manageability of online PDP elements by developing a tool that is able to monitor and assess the content quality. With the monitoring tool, Signify has a tangible asset that is ready to be implemented and used by the sales and marketing employees. Mass monitoring of the online PDPs is facilitated by using scraped PDP data and transform this into useful insights with the help of two dashboards and several drill-down tabs. With the tool, employees at Signify are now able to track how well different retailers are scoring on the content quality and can directly take actions to improve the content based upon different lists of products that have insufficient content quality. This was not possible before and compared to manually checking PDPs, this tool is saving a lot of time. Besides the ability to manage and assess the content quality score, also the ability to compare and benchmark scores and results between different retailers in the overall dashboard is something that will stimulate the focus on improving the content quality within Signify.

The practical value of this research lies in the fact that it delivers a tool to give insights into the online content quality of products and other elements that are present on the PDPs of different retailers. The study offers a theoretical contribution to the literature of online content management in general and specifically in relation to online product detail pages by combining research from different domains to design a tool for monitoring and assessing online content quality.

The research is limited by the immature research domain in the field of online content monitoring. There is little scientific literature available about measuring and using PDP elements to assess the online content quality. Secondly, the tool could not be validated over a longer period due to time constraints and therefore a second iteration of testing (beta test) was not possible. To overcome this limitation, future research should include extra testing of the tool to enhance the validity and generalizability of the tool. Furthermore, it could be interesting to test if using the tool and improving the online content quality is directly correlated with improving the conversion rate at retailers.

Abbreviations

Abbreviation	Meaning
PDP	Product Detail Page
ERT	Electronics Retailer
DSS	Decision Support System
KAM	Key Account Manager
GQM	Goal Question Measurement
KPI	Key Performance Indicator
SME	Small and Medium-sized Enterprises

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1. Introduction

The digital transformation has enabled new possibilities of transactions and processes. With the increasing success of new digital business models, also the attention is growing in marketing and organizational research regarding the factors that caused success in e-commerce (Zumstein & Kotowski, 2020). Baker (2018) has identified nine different factors, divided into indirect- and direct factors, that influence the sales velocity of a product at an online retailer (e.g. Amazon, bol.com, Coolblue) and therefore the success of a product. Most of these factors are found on a product detail page (PDP). A PDP is a web page on an online retailers' website that provides information on a specific product. On these pages different PDP elements are present. Among these PDP elements are the product title, product information, images, reviews, pricing, shipping information and other relevant information that customers want to know before purchasing the product. The PDP elements together determine the quality of the content of the PDP. In Appendix A an example of a PDP is shown. In similar research, Maio & Re (2020) also mention the PDP factors that influence the conversion rate and sales velocity within e-commerce in their research. According to recent market research by Wunderman & Thompson (2019), 89% of the online consumers in the Netherlands find product information on retailers' site important during the buying process, this ranks just behind the price (94%). Furthermore, the research states that 78% of the consumers say that they use product reviews in their buying process, 89% of the consumers think that accurate product information is important and 85% says that the product content on the website is important. These numbers reflect the importance for the retailer and the manufacturing company to optimize the elements that determine the content quality on the PDPs to increase sales and stay competitive. The quality and presence of these PDP elements are directly linked to the conversion rate on the online retailers' site and therefore also the online product sales performance (Di Fatta et al., 2018; Maio & Re, 2020; Baker, 2018).

Monitoring and managing the content quality at different online retailers, from the viewpoint of the seller, could be very valuable to increase the conversion rate and sales velocity of product. Currently, the global leader in lighting, Signify, has a product portfolio of smart lights (i.e., lights that can be connected to the internet) of around 275 SKUs across more than 14 different online retailers in the Netherlands and Belgium. On a typical PDP, around 8 elements are present. Missing product images or videos, no product reviews, incorrect product titles and product descriptions are some of the examples that lead to insufficient content quality of the PDP. The cause of insufficient content quality of a PDP, in most cases, is due to incorrect or incomplete information upload by sales and marketing employees to online retailers or by employees of the online retailer itself. Furthermore, retailers like Amazon and Bol.com, that allow independent third-party sellers to sell their products via their

channel, are also giving the ability to these sellers to change product information on PDPs. This leads to Signify not having the complete ownership of the content on the PDPs.

1.1. Problem statement

The current problem Signify is facing, regarding PDPs with insufficient content quality, is the inability to monitor and manage PDPs in a sustainable and workable way. To monitor, manage and improve the content quality of the PDP, currently a salesperson must check a PDP manually to see if the content quality is sufficient and would report the insufficiencies manually. For Signify, it would be too time consuming as it would take days or weeks to do this for all retailers (around 35000 PDP elements). Currently, content quality insufficiencies on PDPs currently are discovered by “accident” or not discovered at all since there is no systematic approach to monitor the PDPs by sales and marketing employees. For Signify, this inability creates the need to be able to monitor and manage the PDP elements on a regular basis to improve the content quality and therefore the sales velocity and conversion rate.

The problem definition for this research has been defined as follows:

Lack of control and absence of the ability to monitor and manage the online content on PDPs can lead to low PDP content quality which ultimately leads to lower conversion rates of the product.

Solving this problem is expected to result in the ability to monitor and manage the content and therefore the overall conversion rate and sales velocity to ultimately increase the sales performance.

1.2. Research goal and research questions

This thesis is structured along the research goal, main research question and five sub-research questions. The sub-research questions form the ‘skeleton’ around which information is found that will help with answering the main research question and to achieve the research goal.

1.2.1. Research goal

For this thesis, the objective is to design a tool that salespeople can use to monitor and manage the PDP content quality across multiple online retailers in the Netherlands and Belgium for the smart lighting portfolio (i.e., Philips Hue and WiZ products). Monitoring and managing these product page elements to optimize the PDP’s content quality contributes to increasing the conversion rate. The tool should make monitoring of the PDP content quality and identifying the improvements easy (identify exact elements that need improvement) and help to reduce the time that PDPs with insufficient content quality are online. The problem has been scoped to the possibilities that lay within this research so that it was large enough to have a significant impact for the sales department once solved and small enough to be solved within the timeframe (Van Aken et al., 2007).

1.2.2. Research question

Since Signify lacks the ability to monitor and manage the online content on PDPs, a tool is needed to make it possible for the sales employees to manage the content quickly and easily without having to manually check every PDP by themselves. This study will focus on the design of a software tool to serve the employees in monitoring and managing the online content on PDPs. This resulted in the following research question that will be answered in this research:

How can a software tool be designed to facilitate mass monitoring of online product detail page elements to manage the product page content quality and therefore improve the conversion rate?

1.2.3. Sub-research questions

To help in answering the main research question, five sub-research questions are formulated.

Research question 1 (RQ1):

To understand the current issues of managing content on PDPs by the sales and marketing department, it is necessary to understand the current way of working and the associated problems that arise. To identify and analyze these problems, interviews will be held with employees regarding the current process of managing content online. The research question is divided into two sub-questions and is defined below.

1. *What is the current way of managing content at PDPs?*
 - 1.1. *How are PDP elements currently managed?*
 - 1.2. *Which PDP elements can be directly managed upon by Signify?*

Research question 2 (RQ2):

To identify which elements on the PDP need to be monitored and implemented in the tool, it is important to know what the determinants of online content quality are and how these elements influence the conversion rate and sales velocity. The corresponding research question is stated below.

2. *Which PDP elements are determinants of the PDP content quality affecting conversion rate and sales velocity?*

Research question 3 (RQ3):

To ensure that the output of the tool is trustworthy and reliable, the quality of the data is important. The decisions that will be taken by the users of the tool based on the outcomes that the tool presents are heavily relying on the reliable and useful data. The determination of the data quality dimensions important for the tool are based on literature and through interviews with the users of the tool. The research question is presented below.

3. *Which data dimensions are relevant for the data quality of the tool?*

Research question 4 (RQ4):

The purpose of the tool is to give insights that will be used to monitor and improve the online content quality. The insights the tool provides depends on how the scraped data will be used. To ensure that the right calculations are made, rules on how to assess the content quality must be determined. The corresponding research question is stated below.

4. *How can PDP content quality be assessed?*

Research question 5 (RQ5):

For the interface and layout of the tool, different design approaches are possible. The tool design depends on the purpose of tool and the needs of the user. To ensure that the data that the tool displays the most important information in an effective and visually appealing way, an understanding of different tool design aspects is needed. The research question is presented below.

5. *How can the tool interface be designed?*

To answer these questions, the design science research methodology initiated by Simon (1996) was used as the basis for the research design. The aim of the design science research approach is to develop knowledge to design interventions to solve business problems and to design innovative artifacts to solve practical problems (Denyer et al., 2008; March & Smith, 1995). To structure this approach, the problem-solving cycle from Van Aken et al. (2007) was used. The problem-solving cycle tries to develop scientific knowledge in aid of creating design propositions that establishes guidelines for developing the final solution (Van Aken & Romme, 2012). The data for this research was collected through a literature study, semi-structured interviews with Signify employees and internal company data. With the collected data, frameworks and models, the monitoring tool was designed. After designing the tool, it was tested by the end-users of the tool on different criteria.

1.3. Relevance

The theoretical contribution of this study consists out of the determination of requirements and the design for a tool to monitor PDP elements to improve the PDP content quality and therefore the conversion rate. Since the amount of literature about monitoring content quality was scarce, this study adds value to literature by combining theory from different research domains and empirical research into a practical tool to solve the research problem. For Signify, the implications are that a tangible asset in the form of a tool will be designed specifically for the sales & marketing department for online retailers and ERT-channels for the Philips Hue and Wiz product portfolio. The tool will deliver

quick insights in the content quality across different online retailers and serves as a solution for managing the PDP elements.

1.4. Report structure

The report is structured as follows. Chapter 2 describes the theoretical analysis that serves as the basis for this study and as input for the empirical research. The research methodology is discussed in Chapter 3 and explains in detail how the research is conducted. Next, in Chapter 4, the data that was collected during the interviews is used as input together with the theoretical analysis to answer the research questions and to determine the design requirements. The initial solution design is tested and validated by users in Chapter 5 whereafter the final solution design of the monitoring tool is presented. Lastly, the conclusion and discussion of this study are presented in Chapter 6.

2. Theoretical analysis

The theoretical analysis discusses the research from literature and aims to get an understanding of the current scientific and practical knowledge regarding content management and tool design. Knowledge on four main different topics is gathered and elaborated to serve as input for the empirical research and the design of the tool.

2.1. Conversion rate and its antecedents

In e-commerce, the conversion rate represents the proportion of orders in relation to the total number of website visitors. For instance, if 100 people visit a product page and 4 of them place an order for that product, the conversion rate is 4% (Ayanso & Yoogalingam, 2009). Research on the factors that influence the conversion rate of e-commerce websites has been extensively done. Di Fatta et al. (2018) state that the conversion rate is determined by so called “promotional factors” and “quality factors”. Promotional factors consist of the possibility of free shipping, free return, having a discount policy and seasonality, whereas quality factors consist of the speed of load (i.e. the loading speed of the website), and the difference between luxury products and mainstream products. Furthermore, Gudigantala et al. (2016) found that website satisfaction positively influence the conversion rate of e-commerce retailers. Website satisfaction is defined as an affective evaluation which is a result of the consumer’s overall interaction with a website. Muylle et al. (2004) conceptualize website satisfaction as the satisfaction with the website layout, the information (relevancy, accuracy, comprehensibility and comprehensiveness, the connection (ease-of-use), structure and speed) and language customization.

Baker, (2018) states that different factors determine the sales velocity of a product, in this case at Amazon.com. Sales velocity is relative to the competition for the same search term and it is also a measure of conversion rate. Amazon.com uses the sales velocity of a product to determine the position of similar products in the search ranking. Baker (2018) distinguishes two types of factors that influence the sales velocity: direct- and indirect factors. An overview is of the direct- and indirect factors is shown in Figure 1.

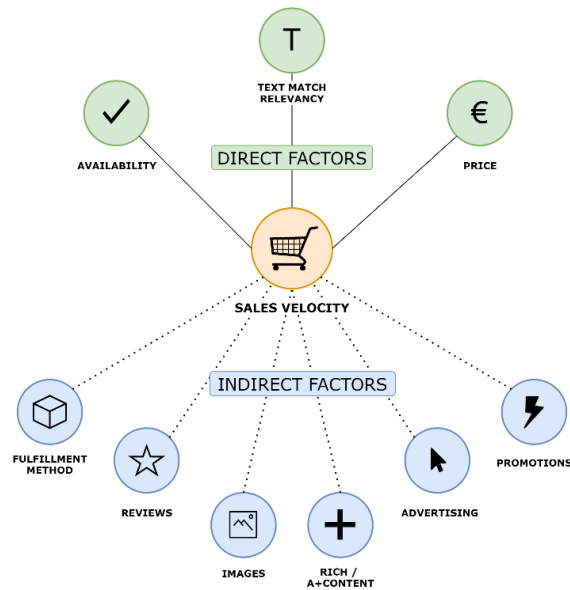


Figure 2 - Direct- and indirect factors affecting sales velocity (Baker, 2018)

The direct factors consist of availability, text match relevancy and the price. The availability of a product is concerned the availability rate of the product. Consumers may reduce future purchases and influence other consumers with negative comments when a product is not available (Liu & Zinn, 2001). Having a high availability rate helps with the sales velocity. Text match relevancy is concerned with the product title, product features and the product description. It is a valuation done to check how good the content of your product listing is. It shows the listings on the top results if its content matches the search terms or keywords searched by the users (Nagaraj, 2019). The price is a factor that speaks for itself. If a product is competitively and aptly priced, chances are higher that this will positively influences the sales velocity.

The indirect factors of sales velocity, according to Baker (2018), consist of the type of fulfilment method, reviews, images, rich /A+ content, advertising, and promotions. The type of fulfilment depends on if the stock is stored and shipped via an Amazon warehouse or not. Having stock stored and shipped via an Amazon warehouse leads to a “featured merchant” status which helps in reaching Amazon prime members and winning the buybox. It ultimately leads to better sales velocity and conversion (Nagaraj, 2019). Reviews help with consumer trust for online products, since the consumer is not able to see or feel the product in person when shopping online, reviews can help with the trust (or distrust) a consumer perceives. Currently online ratings and reviews on retailer websites (52%) were included among the top three sources of information most frequently by respondents—ahead of advice from friends and family members (49%) and advice from store employees (12%). Furthermore, 70% of online consumers indicate that they trust online product reviews (Floyd et al., 2014). According to Watson et al. (2018), the user rating of the product is more important than the

number of reviews a product has, but the number of reviews is perceived to be diagnostic and will influence consumer assessments (Santana et al., 2020). The number of images on a PDP is important to reduce the mental intangibility that consumers experience during online shopping. Song & Kim (2012) find out that multiple product images can be used to reduce that mental intangibility and increase the perceived amount of information in an online shopping environment. Furthermore, a positive effect for the use of contextual imagery backgrounds versus products with a white background is found by Maier & Dost (2018). Ambiguous or difficult to recognizable products profit even more when contextual images are present as this facilitates recognition by the consumer. For this reason, it is important for a retailer to present products with contextual imagery. Rich content or A+ content is defined as additional, high-quality image content on a PDP that gives buyers a better understanding of what they're buying to give them more confidence that they are getting the product they were hoping for. Advertising is the most powerful lever that can increase the sales velocity and conversion rate. Placing advertisements on products however brings additional costs to the seller in the form of advertising costs. Promotions or discounts also help with increasing the sales velocity since this gives the product a temporary price drop. This however is not a sustainable and long-term strategy for improving the sales velocity since the seller is cutting in on the margin of the product (Nagaraj, 2019).

Maio & Re (2020) focus in their research only on the influence of the content on the PDP in relation to the conversion rate and the click-through rate at Amazon.com. The factors on the PDP that determine the click-through rate and the conversion rate are represented in the model below. As Figure 2 shows, the main image is important for the click-through rate of customers that click on the main image and to go to the corresponding PDP. When on the PDP, additional images, bullet points, product description and enhanced brand content are factors that influence the conversion rate. These factors from the PDP match the factors stated by Baker (2018) to be the drivers of the conversion rate.

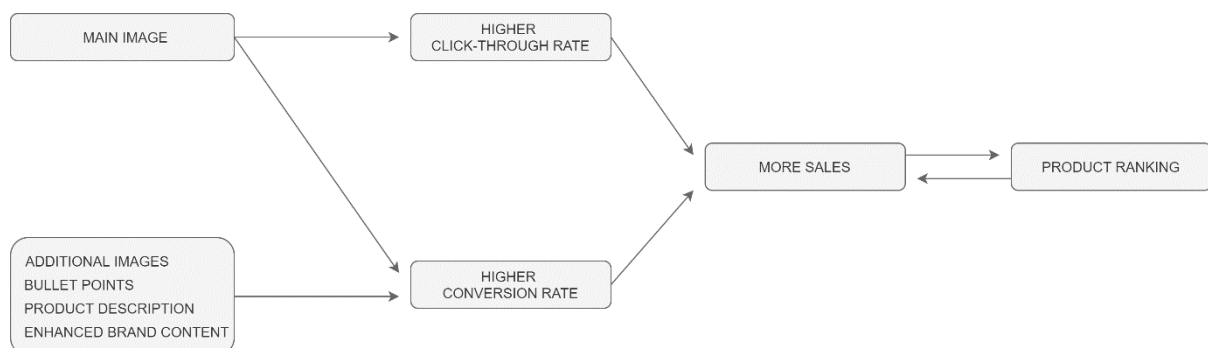


Figure 3 - Factors influencing conversion rate and click-through rate (Maio & Re, 2020)

To make a distinction between PDP factors and other factors that influence the conversion rate of a product, a visual representation has been designed (Figure 3). This model is based on the sales velocity model from Baker (2018) and the sales model from Maio & Re (2020).

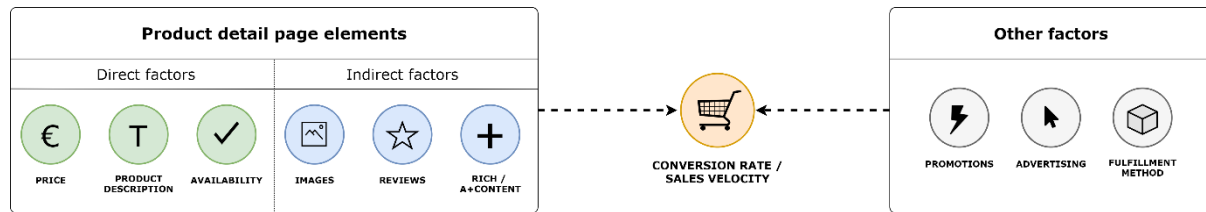


Figure 4 - PDP elements affecting conversion rate and sales velocity

2.2. Data-driven decision support systems

The purpose of the tool is to get insights into the online content quality of PDPs and make decisions based on these insights. To help the users in making these decisions, a decision support system (DSS) forms the basis for the tool. A DSS is an information system that supports business or organizational decision-making activities. A DSS must provide current, timely information and analyses that are accurate, relevant and complete. Furthermore, the information that is presented within a DSS can vary from analysis of transactional data, data resulting from decision models or data from external sources (Power, 2002). According to Power (2002), there are five different types of DSS with each of them having different characteristics: communications-driven DSS, data-driven DSS, document-driven DSS, knowledge-driven DSS and model-driven DSS. In Appendix B, an overview is given of the different types of DSS. The purpose of a data-driven DSS is to analyze large amounts of structured data and enhance a person or group's ability to make decisions based on data. Furthermore, data-driven DSS help users retrieve, display and analyze (historical) data (Power, 2002). Since the scraped data consists of large amounts of timely data and the purpose of the tool is to give the user the ability to display and analyze different data, this type of DSS fits best for the tool that is designed in this research. To get these insights into the online content quality of PDPs, an understanding of the frameworks and features of a data-driven DSS are of importance during the design process the tool.

2.2.1. Data-driven decision making

Mandinach et al. (2006) have come up with a conceptual framework for data-driven decision-making for a tool. The conceptual framework consists of three main elements that together form a continuum: data, information and knowledge. This continuum is based on the theory by Ackoff (1989), who stated that data, information and knowledge together form a continuum where data is transformed to information and ultimately to knowledge that can be used to make decisions. In the Figure 4 below the continuum is stated.

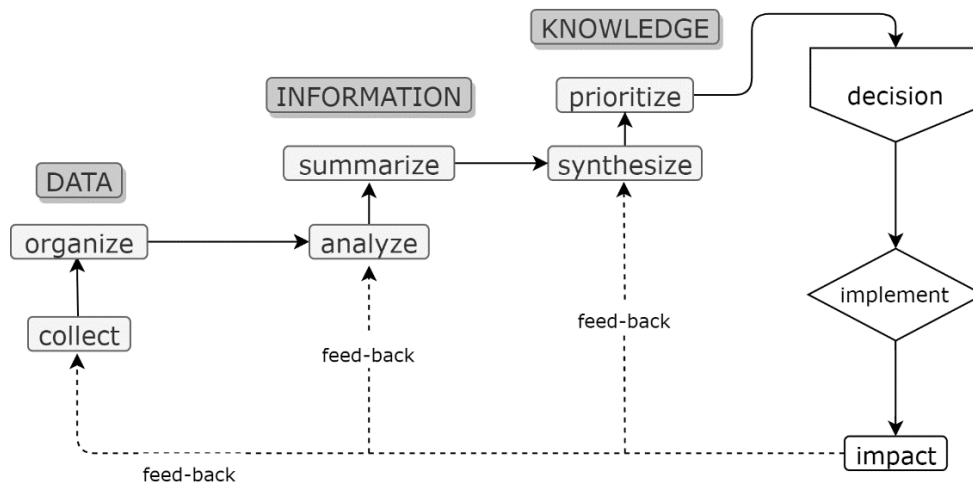


Figure 5 - Data-driven decision-making continuum (Mandinach et al., 2006)

Based on research by Light et al. (2004), the definitions of data, information and knowledge are described as follows:

Data in itself exists in a raw state. It does not have meaning by itself and therefore can exist in any form, usable or not. Whether data becomes information or not depends on the understanding of the person looking at the data.

Information is data that is given a meaning when connected to a context. It is data that is used to comprehend and organize our environment, unveiling an understanding of relations between data and context. Information on its own however does not carry any implications for future action.

Knowledge is the collection of information deemed useful and is eventually used to guide certain actions. Knowledge is created through a sequential process.

Every point along the data to knowledge continuum has two relevant skills that are crucial to the decision-making process. On the data level “collect” and “organize” are relevant skills, for information these are “analyze” and “summarize” and for the knowledge level “synthesize” and “prioritize” are the skills that are deemed as relevant (Mandinach et al., 2006). The first step is that the stakeholder(s) of the project must decide which data needs to be *collected*. The data can be newly collected data or use historical data from existing data sources. Once the data has been collected, it is necessary to *organize* the data in a systematic way so that the data is structured and that it makes sense. If the collected data is not structured or has not been pulled together in a sensible matter, it is difficult to extract meaning from it. The next step is to *analyze* the systemically structured data for informational purposes. The scope of the analysis may be broad or constrained, depending on the type of inquiry and the role of the decision maker (user). After the analysis there will be some sort of data *summarization* of all accumulated information since too large amounts of data cannot properly be

interpreted and therefore transformed to usable knowledge. To last steps to turn information into knowledge are that the stakeholder(s) must *synthesize* the available information into one data source and *prioritize* the knowledge. Setting priorities often requires a value judgement on the information and knowledge. Prioritization allows the decision makers to determine what is most important, most pressing or most prudent to the particular decision that needs to be taken. The outcome of the six steps, moving from data to knowledge, is a decision. The decision is *implemented*, and this will result in an *outcome* or *impact*. Depending on the outcome or impact, the decision maker may decide that it needs to return to one of the six steps and thereby creating a feedback loop. Because of the feedback loops, data-driven decision making is seen as an iterative process with data leading to a decision, implementation of that decision or determination of the impact and therefore perhaps need to work through some or all of the six processes again (Mandinach et al., 2006).

2.2.2. Features of a data-driven DSS

Research on information systems have led to a better understanding of the features managers expect from data-driven DSS. Partly based by research on Online Analytical Processing (OLAP) software by Codd et al. (1993), Power (2008) presents 11 major data-driven DSS features from a user perspective. These features are stated in Table 1 below.

Table 1 - Data-driven DSS features (Power, 2008)

Data-driven DSS feature	Description
Ad hoc data filtering and retrieval	The system helps users systematically search for and retrieve data, filtering is done using drop down menus. Users can change the aggregation levels, ranging from most summarized to the most detailed.
Alerts and triggers	The system helps users to establish rules for email notifications and other predefined actions.
Data displays	Users can choose between different data displays like scatter plots, bars and pie charts. The type of data display depends on the type and amount of data that needs to be presented.
Data management	Since users usually have limited “working storage” for a data subset, users may be able to

	group data or change the data format in order to make it workable.
Data summarization	Users can view or create pivot tables and cross tabulations. Users can create custom aggregations and calculated computed fields, totals, and subtotals. Users can view a slice of data but are also able to drill-down for more detailed data from a summarized value in a table.
Excel integration	Users are able to extract and download data in Excel format for further analysis.
Metadata creation and retrieval	Users are able to add metadata to analyses and reports they create. Metadata is an explanation of the data in a DSS data store. Some metadata is used to label the screen displays and report headings.
Report design, generation and storage	Users can interactively extract, design, and present the information from the DSS in a report with tables, text and different types of charts.
Statistical analysis	Users are able to calculate descriptive statics to summarize or describe the data and create trend lines.
View predefined data displays	The data-driven DSS displays a dashboard to monitor the operational performance. The dashboard integrates information from multiple sources and metrics into charts, gauges and KPIs.
View production reports	DSS designers may create periodic reports as part of a data-driven DSS for the users to access.

Implementing the above features or a subset thereof in the design of a data-driven DSS, depending on the needs of the user and the purpose of the system, will help managers monitor operational

performance or gain intelligence from historical data. Decisions that are made using a data-driven DSS can be affected by factors that are unrelated to the actual data. So as part of the design of these systems, careful consideration to how data is framed and displayed with the help of the above-mentioned features must be given (Power, 2008).

2.3. Quality of data

The quality of data used for the tool is a critical aspect for the usefulness and success of the tool since the quality of the input data determines the quality of the analyses that the tool will eventually make. As decisions are based on the available data and information, low quality data and information negatively impact the organization’s efficiency (Redman, 1997). The growing importance of data quality has resulted in the development of a conceptual framework that captures the aspects of data quality that are important to the data consumers (Wang & Strong, 1996).

2.3.1. Data quality dimensions

Data quality can be categorized into four different categories following the data quality framework by Wang & Strong (1996). The data quality framework is shown in Figure 5.

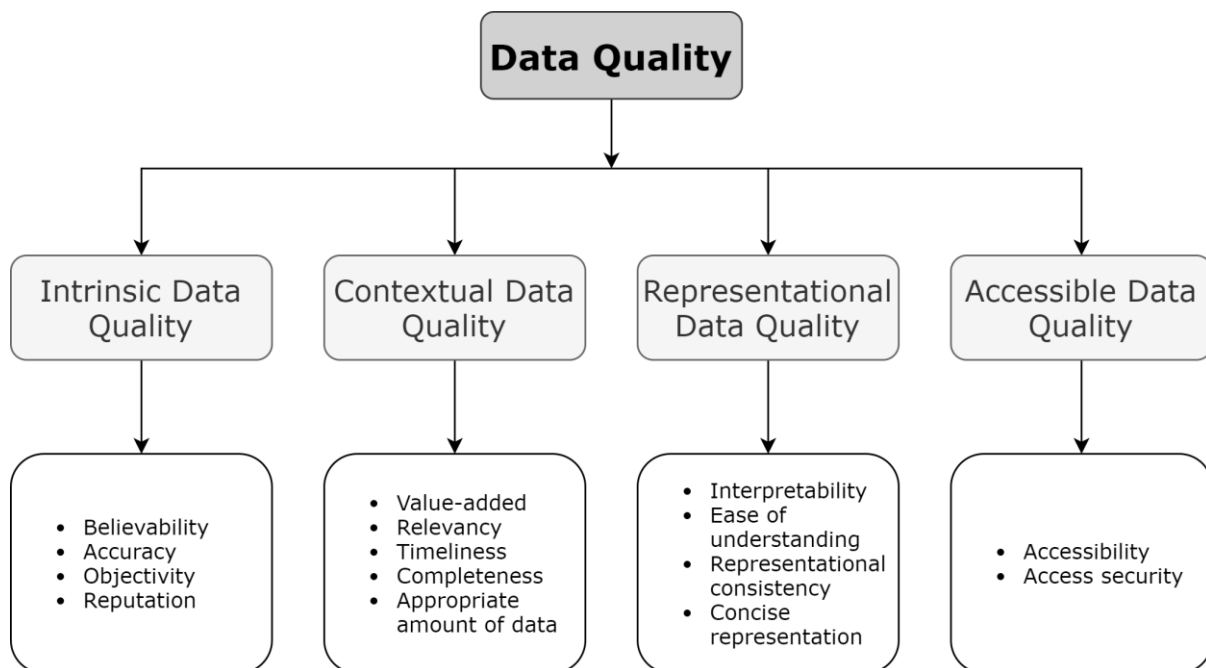


Figure 6 - Data quality framework (Wang & Strong, 1996)

Wang & Strong (1996) state that data must be accessible, intrinsic, contextual, and representational. For each of these categories, data quality dimensions are stated. Each data quality dimension captures a specific aspect included under the general umbrella of data quality (Batini & Scannapieco, 2006). An explanation of the four different categories is stated below.

- *Intrinsic data quality*: Intrinsic data quality is about the quality of the data that it has on its own. For example, accuracy is a quality dimension that is intrinsic to data and there is no different interpretation of the data dimension possible (Batini & Scannapieco, 2006).
- *Contextual data quality*: Contextual data quality considers the context where data is used. For example, the completeness of data is related to the context of the task. This means that the data can be complete for one task but for other tasks there may be some missing and crucial data (Batini & Scannapieco, 2006).
- *Representational data quality*: Representational data includes aspects related to the format of the data (concise and consistent representation) and meaning of data (interpretability and ease of understanding) (Wang & Strong, 1996).
- *Accessible data quality*: Accessible data quality is related to the accessibility of data and to a further non-functional property of data access (Batini & Scannapieco, 2006).

There is no general agreement in literature either on the exact meaning of each data quality dimension, the dimensions are not defined in a measurable or formal way and are defined by means of descriptive sentences in which the semantics are consequently disputable (Batini & Scannapieco, 2006). For this reason, definitions from different sources are used to describe each of the data quality dimensions in the conceptual framework from Wang & Strong (1996). Identifying the data dimensions relevant for the tool will help with assessing the data quality and improving on this where needed. The different definitions for the data quality dimensions are shown in Table 2.

Table 2 - Data quality dimensions

<u>Data quality dimension</u>	<u>Definition</u>
Believability	Data is accepted or regarded as true real and credible. (Wang & Strong, 1996)
	Believability is the extent to which data is accepted or regarded as true, real and credible. (Scannapieco & Catarci, 2002)
Accuracy	The extent to which data is correct, reliable and certified free of error. (Wang & Strong, 1996)
	Refers to the degree with which data values agree with an identified source of correct information. There are different sources of correct information: database of record, a similar, corroborative set of data values from another table, dynamically computed values, the result of a manual workflow and irate customers. (Loshin, 2001)
Objectivity	Data is unbiased and impartial (Wang & Strong, 1996).

	Objectivity is the extent to which data is unbiased (unprejudiced) and impartial. (Scannapieco & Catarci, 2002)
Reputation	Data is trusted or highly regarded in terms of their source and content. (Wang & Strong, 1996)
Value-added	Data is beneficial and provide advantages for their use. (Wang & Strong, 1996)
Relevancy	<p>Relevance is the degree to which statistics meet current and potential users' needs. It refers to whether all statistics that are needed are produced and the extent to which concepts used (definitions, classifications etc.) reflect user needs. (Lyon, 2008)</p> <p>The Characteristic in which the Information is the right kind of Information that adds value to the task at hand, such as to perform a process or make a decision. (English, 2009)</p>
Timeliness	<p>The information is processed and delivered rapidly without delays. (Eppler, 2006)</p> <p>Timeliness reflects the length of time between availability and the event or phenomenon described. Punctuality refers to the time lag between the release date of data and the target date when it should have been delivered. (Lyon, 2008)</p> <p>Timeliness refers to the time expectation for accessibility and availability of information. Timeliness can be measured as the time between when information is expected and when it is readily available for use. (Loshin, 2006)</p>
Completeness	<p>Completeness refers to the degree to which values are present in a data collection, as for as an individual datum is concerned, only two situations are possible: Either a value is assigned to the attribute in question or not. In the latter case, null, a special element of an attribute's domain can be assigned as the attribute's value. Depending on whether the attribute is mandatory, optional, or inapplicable, null can mean different things. (Redman, 1997)</p> <p>Completeness of data refers to the extent to which the data collected matches the data set that was developed to describe a specific entity. Monitoring for incomplete lists of eligible records or missing data items will identify data quality problems. (HIQA, 2011)</p>

	Degree of presence of data in a given collection (Scannapieco & Catarci, 2002)
Appropriate amount of data	The quantity or volume of available data is appropriate. (Wang & Strong, 1996)
Interpretability	Data is in appropriate language and unit and data definitions are clear. (Wang & Strong, 1996) Interpretability of data refers to the ease at which the user can understand the data. Is there any ambiguity in understanding the data and is there information available to help the user understand the terminology? (HIQA, 2011)
Ease of understanding	Data is clear without ambiguity and easily comprehended. (Wang & Strong, 1996)
Representational consistency	Data is always presented in the same format and are compatible with the previous data. (Wang & Strong, 1996)
Concise representation	Data is compactly represented without being overwhelmed. (Wang & Strong, 1996) Is the information to the point, void of unnecessary elements? (Eppler, 2006)
Accessibility	Data is available or easily or quickly retrieved. (Wang & Strong, 1996) Accessibility of data refers to how easily it can be accessed; the awareness of data users of what data is being collected and knowing where it is located. (HIQA, 2011) Accessibility expresses how much data is available or quickly retrievable. (Scannapieco & Catarci, 2002)
Access security	Access to data can be restricted and hence kept secure. (Wang & Strong, 1996)

2.4. Dashboard design

A well-known management principle states that you cannot manage what you cannot measure. Malik (2005) however also states that “you cannot manage well what you cannot monitor and that is where enterprise dashboards come in”. The definition of a dashboard by Steven Few & Edge (2007) is “a visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen”. Dashboards have become the vehicle of execution for several activities within organizations worldwide (Malik, 2005). Brath & Peters (2004) state that

dashboards and its visualizations are cognitive tools that improve the span of control over business data for the user. In the case of this research, a dashboard should display the most important information from different data sources in one screen to achieve predefined objectives. In this chapter the method to design an enterprise dashboard and the different characteristics specific to an enterprise dashboard are stated.

2.4.1. Effective dashboard design

In order to design a useful dashboard, Janes et al. (2013) state that two aspects are important in the design process: selecting the right data and choosing the right visualization technique.

2.4.1.1. *Selecting the right data*

Besides checking and improving the data quality, it is also important to select the right data that serves as input for the tool. Selecting the right data falls within the *relevancy* data quality dimension (Wang & Strong, 1996). To select the right data, a measurement model is developed that defines *which* data needs to be collected and the reason *why* it is collected. Once collected data is linked to the reason why it is needed, it is possible to interpret the data and use it for different projects since the right context is known. The measurement model that is used is based on the GQM+strategies (Basili et al., 2010) approach which is based on GQM (Goal-Question-Measurement) models (Basili et al., 1994). A GQM model is defined on three different levels:

The goal: The goal (conceptual level) defines what is researched and the reason why. What is studied is the object of study, the specific products, processes, and resources. Why something is studied, identifies the reason, the different aspects taken into consideration, the considered points of view, and the environment (Janes et al., 2013).

The question: The questions (operational level) define what parts of the object of study are relevant and what properties of such parts are used to characterize the assessment or achievement of a related goal. These properties are often called the “focus” of the study. Altogether, the questions specify which specific aspects of the object of study are observed to understand whether the goal is achieved or not. Questions are measurable entities that establish a link between the object of study and the focus (Janes et al., 2013).

The measure: The measures (quantitative level) define which data has to be collected to answer the questions in an objective (quantitative) way (Janes et al., 2013).

In Figure 6, the GQM model is visually represented.

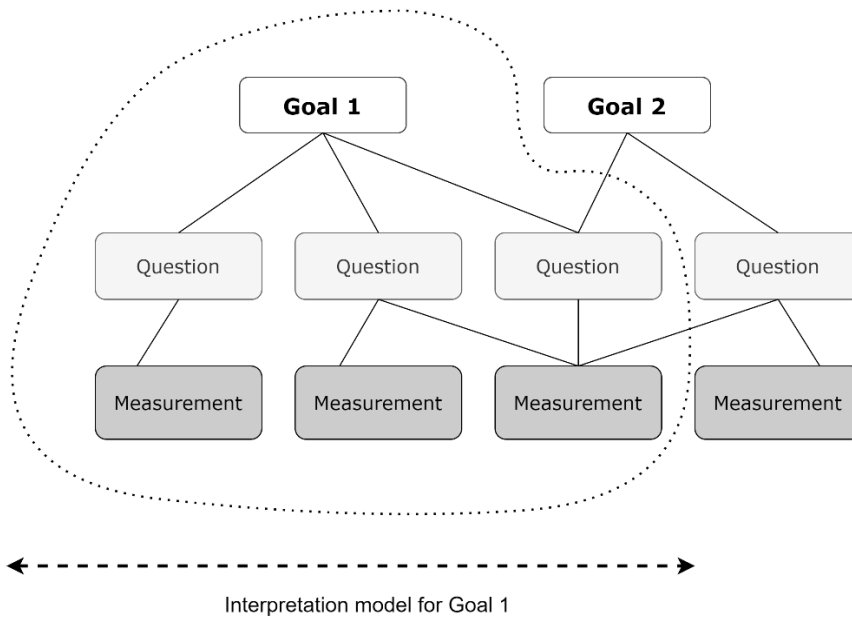


Figure 7 - GQM model (Janes et al., 2013)

Goal hierarchy

Every activity in an organization is a means to an end and a part of the organizational strategy to achieve an organizational goal. For this reason, in every organization a goal hierarchy can be observed. Starting from the main organization goal (e.g. obtaining revenue), all subsequent goals are derived from that main goal (e.g. increasing sales, increasing reliability).

When the goal(s) have been defined, the next step is to define questions that characterize the goal in a quantifiable way and the measurements to describe the data that is used to answer the questions in order to reach the goal. The questions can be categorized in three different groups (Basili & Caldiera, 2000):

- Questions that characterize the object of study with respect to the overall goal.
- Questions that characterize relevant attributes of the object of study with respect to the focus.
- Questions that evaluate relevant characteristics of the object of study with respect to the focus.

After defining the questions, the last step is to define the type of measurements that are needed to answer the questions. Multiple types of measurements might be used to answer questions and they depend on different factors such as the amount of data that is available and the level of precision that is needed.

2.4.1.2. *Choosing the right visualization*

Dashboards can be designed in different ways; it depends on the requirements on which elements or characteristics it has. There are two usage scenarios for a dashboard: “pull” and “push” (Janes & Succi, 2009).

In a pull scenario, the user wants to get a specific piece of information and uses the dashboard to obtain it. Different aspects of technology acceptance become important in this case, such as the dashboard’s perceived usefulness and perceived ease of use (Venkatesh & Bala, 2008). The user needs to understand the context of the data and the meaning of the data. This means that the user knows why data is collected, how it should be interpreted and how it can be used in different projects. Furthermore, the visualizations should require minimal effort to get the conveyed message and allow the user to choose the level of detail of the data (Janes et al., 2013). A dashboard with a push scenario, pushes the information to the user. The user should be able to see the dashboard without any effort and the information will be pushed to the user without their active participation. Second, the user should not need to interact with visualizations to understand the dashboard. The chosen charts within the dashboard have to be designed so that interaction is only necessary when the user switches to the “pull” mode of the dashboard (i.e., if the user wants to investigate further on the shown visualizations). Furthermore, the dashboard should attract the attention of the user by displaying dashboard elements in a visually appealing way. Displaying dashboard elements in a visually appealing way can increase the user’s interest in looking at the dashboard. Lastly, arranging data to minimize the time needed to consult the dashboard is an important consideration within a “push” dashboard. The user needs to be allowed to develop habits when using the dashboard and know where to quickly find the needed information (Ware, 2019).

Whether a dashboard is more suited to the push or pull scenario depends on the amount of effort a user has to invest to see the dashboard (Janes et al., 2013). A dashboard that pushes the information to the user has the advantage of informing him in unexpected, unforeseen situations about problems, anomalies, and the like. A dashboard that is designed to support the pull scenario should offer more possibilities to explore the data, to filter and to search and to investigate the reasons that caused the data to be as it is (Janes et al., 2013). For the dashboard in the tool, a “pull” scenario is the most likely option since the users want to obtain specific information about the PDPs and will use the dashboard for this purpose. In the future however, the dashboard could be more leaning towards a “push” scenario when the content quality for most online retailer is satisfactory. In this scenario negative changes in the content quality of PDPs will be “pushed” to the user via alerts or triggers so that the tool can be used to a lesser extent.

2.4.2. Dashboard characteristics

Malik (2005) states that the characteristics specific to enterprise dashboards can be divided into two categories: basic characteristics and enhanced characteristics. The basic- and enhanced characteristics are essential for the success of the dashboard. To make it easier to remember the characteristics, the basic characteristics are established under the acronym “SMART” and the enhanced characteristics are captured in the acronym “IMPACT” (Malik, 2005). The basic- and enhanced characteristics for the design for a successful enterprise dashboard are defined as follows:

Basic (SMART) dashboard characteristics

Synergetic: The dashboard must be ergonomically and visually effective for a user to synergize information about different aspects within a single screen view.

Monitor KPIs: The dashboard can display critical KPIs required for effective decision making for the domain to which a dashboard caters.

Accurate: Information being presented must be entirely accurate in order to gain full user confidence in the dashboard. Furthermore, the supporting dashboard data must have been well tested and validated.

Responsive: The dashboard must respond to predefined thresholds by creating user alerts in addition to the visual presentation on the dashboard (e.g., sound alarms, e-mails) to draw user attention to critical matters.

Timely: Must display the most current information possible for effective decision making. The information must be real-time and right-time.

Enhanced (IMPACT) dashboard characteristics

Interactive: The dashboard should allow the user to drill down and get to details and root causes.

More data history: The dashboard should allow users to review the historical trend for a given KPI.

Personalized: The dashboard presentation should be specific to each user’s domain of responsibility, privileges, data restrictions, and so on.

Analytical: It should allow users to perform guided analysis such as a what if analysis. The dashboard should make it effortless for a user to visually navigate through different drill-down paths, compare, contrast, and make analytical inferences. In this way, the dashboard can facilitate better business comprehension within a set of interdependent business variables.

Collaborative: The dashboard should facilitate users' ability to exchange notes regarding specific observations on their dashboards. This could also be adopted to accomplish workflow checks and process controls.

Trackability: It should allow each user to customize the metrics he or she would like to track. Such customized tracking could then be incorporated within the default dashboard view presented to the user after login.

2.4.3. Dashboard presentation

The last step, after determining the right data, visualization, and characteristics, is the presentation of the dashboard. The dashboard presentation can be broken down into three categories: design, layout and navigation (Malik, 2005).

2.4.3.1. Dashboard design

The dashboard must have an aesthetic appeal and deploy powerful visualization to convey the needed information within a limited space. Four key elements are identified that are important for the design of the dashboard:

- *Screen graphics and colors:* Screen graphics and colors are important in building the visual framework of the dashboard. The color palette should not interfere with or distract from the key messages and information displayed on the dashboard. Charts and other key message delivery systems should have their own color scheme to differentiate them from background, aesthetic, or functional elements (Malik, 2005).
- *Appropriate chart types:* Depending on the information being presented, certain chart types are more appropriate than others. For example, if a trend needs to be shown, a line chart may be the best choice. If two metrics need to be compared, a column or bar chart is most obvious choice (Malik, 2005).
- *Animation with relevance:* Animation with relevance used advanced capabilities (if this is provided by the software) to interact with the user. For example, when hovering the mouse over certain charts or KPIs, corresponding metrics will be shown or highlighted (Malik, 2005).
- *Optimal content placement:* Limit to the content that is relevant. Keep out for overloading a single dashboard screen with too much content that may create a sense of clutter that overwhelms the user. The most important KPI's need to be on top and on the first screen (Malik, 2005).

2.4.3.2. *Dashboard layout*

The dashboard layout can be considered as part of the dashboard design, however specific details related to just the layout of the dashboard are identified and therefore this is seen as a separate category. There are four key elements identified by Malik (2005) that are important for the layout of the dashboard:

- *Number of windows and frames within the dashboard:* On a single dashboard screen there is space to put in multiple windows or frames. Different charts, reports and KPIs can be placed here. It is important that these windows or frames are not overwhelming the user because every window or frame demands user attention. For this reason, not more than six windows on one dashboard screen should be used. (Malik, 2005).
- *Symmetry and proportions:* Symmetry and proportions of the windows are important to maintain an effective visual presentation. A rule of thumb is to have uniformly sized windows. Irregularly sized windows may lead to unintended highlighting and diminishing of the importance of displayed information (Malik, 2005).
- *Computer screen resolution:* Computer screen resolution is an important consideration for deciding the window placements within a dashboard. Because not every user will have the same screen resolution there will be differences in how the dashboard will be shown for different resolutions. If a dashboard is designed for a high resolution, a user with a lower resolution may have to scroll horizontally and this detracts from the ease of use of the dashboard. To avoid this problem, it is best to design the dashboard for a lower resolution or make the dashboard easily scalable for every resolution (Malik, 2005).
- *Context selection:* Context selection refers to the placement of content among various windows and frames within the dashboard. Dashboards must provide a view into the business, and only the business users know best how they view and interrelate various charts and reports to extract critical business information. It is a good practice to elicit early input and feedback from the user base when designing the dashboard. Context selection and navigation are the two most important areas requiring end-user (Malik, 2005).

2.4.3.3. *Dashboard navigation*

Navigation involves the determination of how the information will be divided across different dashboard screens as well as linking charts and reports to allow the user to drill-down for more advanced analysis. The three key elements identified by Malik (2005) that are important for the navigation of the dashboard are:

- *Information grouping and hierarchy*: Information grouping and hierarchy refers to the creation of dashboard groupings according to the information presented in them. The groupings and hierarchies help determining which group of dashboards falls at what type of the information hierarchy, given the importance and priority of the information content (Malik, 2005).
- *Tabs and pivots*: Tabs and pivots help to design the user experience in navigating across the different dashboard groups. Tabs are links with a brief title on which the user may click to see the corresponding dashboard. Pivots are drop-down lists that allow users to select any one of the listed dashboards to view. If there are many dashboards, pivots offer an advantage because tabs are subject to the limitation of screen width (Malik, 2005).
- *Context drill-down*: Context drill-down refers to the possibility for the user to see additional details when the user clicks on a specific chart or report. A drill-down has two components: a *source* and a *destination*. The source requires capturing the chart or report that has been clicked on along with the specific data point value that the user has clicked on. The data point context is then passed on to the destination, which must have a smart filtering capability to present the information relevant to the data point that was clicked on. The source chart information is subsequently used for the user to navigate back to the point of origin. The destination chart accepts the source data point parameter and presents the filtered chart or report. A context drill-down is essentially a link with added knowledge to a data point on the chart that was clicked on (Malik, 2005).

2.5. Conclusion and contribution

In this chapter theories, frameworks and models from different scientific domains have been identified for the development of software tool to monitor and manage the online content quality. Firstly, it is important to understand and identify which PDP elements are deciding factors for improving the conversion rate. This knowledge provides the basis for determining which PDP elements should be implemented in the monitoring tool (RQ2). Together with expert interviews the final selection of these elements will be set. For the framework of the tool, the data-driven decision making continuum by Mandinach et al. (2006) can be used to determine which steps need to be taken to get from initial raw data to insights (knowledge). Furthermore, different data-driven DSS features are presented which can be implemented within the tool to help the users of the tool to monitor the content quality and make analysis with the data. To ensure accurate and reliable data quality, data quality dimensions are identified that determine the quality of the analyses that the tool will make. Interviews with the users of the tool will be used to determine which of the presented data quality dimensions are relevant for the tool (RQ3). Lastly, to visually present the data to the user, an

understanding of the principles of effectively designing a dashboard is needed to develop the tool. A GQM model can be used to define the goals of the tool and determine the data that needs to be collected to reach that goal. For data presentation, different characteristics for the development of a dashboard are presented for the design, the layout and the navigation (RQ5).

This research contributes to scientific research by filling the gap regarding the implementation of knowledge on monitoring online content into a software tool that can analyze and display the online content quality in a visual effective and attractive way. In current literature this combination of research domains for the development of such a specific software tool has not been researched yet.

3. Research methodology

The research methodology describes in detail how the research was conducted. First, the research approach and the design are explained. After this, the materials and data that were used are explained followed by the research procedure of this study and the participants that were involved. Lastly, the validity and reliability of this research are discussed and elaborated.

3.1. Research approach and design

The research design is based on design science research initiated by Simon (1996). The aim of the design science research approach is to develop knowledge to design interventions to solve business problems and to design innovative artifacts such as systems, constructs, models, methods and instantiations to solve construction problems (Denyer et al., 2008; March & Smith, 1995). Evaluation of the design and communicating the results is also part of design science research (Dresch et al., 2014). The tool can be understood as an artifact which serves to solve the current problem regarding the lack of control and absence of the ability to manage the online content on PDPs.

To structure of the design science approach, the problem-solving cycle from Van Aken et al. (2007) is applied. The problem-solving cycle tries to develop scientific knowledge in aid of creating design propositions that establishes guidelines for developing the final solution (Van Aken & Romme, 2012). It consists out of five steps: (1) problem definition, (2) analysis and diagnosis, (3) solution design, (4) intervention and the (5) evaluation (Figure 7). This approach is commonly used in the academic field to find practical solutions to business problems. Furthermore, the problem-solving cycle is the best suited approach for solving a 'field problem' when it is of a technical or economic nature (Van Aken et al., 2007). Since the goal of this research is both technical and economic in nature, the problem-solving cycle is the most appropriate fit. In Figure 7, the general problem-solving cycle by Van Aken et al. (2007) is shown.

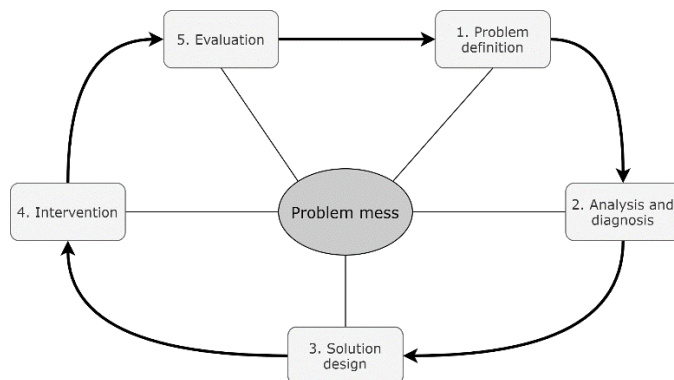


Figure 8 - Problem-solving cycle (Van Aken et al., 2007)

Since the problem-solving cycle is a fairly general design approach for a wide range of business problems, an additional research process model by Moultrie et al. (2007) is used to make the research design more specific for this study. Moultrie et al. (2007) discuss and develop a model for the design of an audit tool for small and medium-enterprises (SMEs). The design process of an audit tool is comparable to the design process of a monitoring tool and therefore this research process model fits the research objective for this research and therefore adds value to the problem-solving cycle. The research process based on the model by Moultrie et al. (2007) consists of three phases: the exploratory study, tool development & testing and the validation, as shown in Figure 8. The model fits well with the objective of this study to create a tool where it is important to iteratively review, modify and apply changes to the tool based on input from the users.

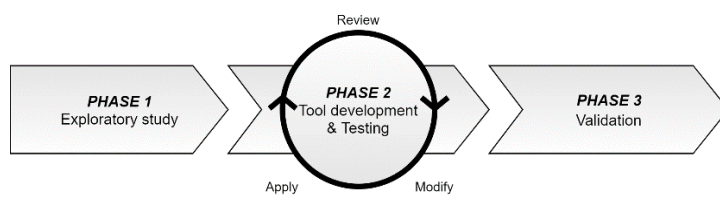


Figure 9 - Research process model (Moultrie et al., 2007)

The combination of the problem-solving cycle and the research process model forms the research design for this study as shown in Figure 9. Both models are complementary to each other since the model from Moultrie et al. (2007) is based, just as the problem-solving cycle from Van Aken et al. (2007), on the design science research approach.

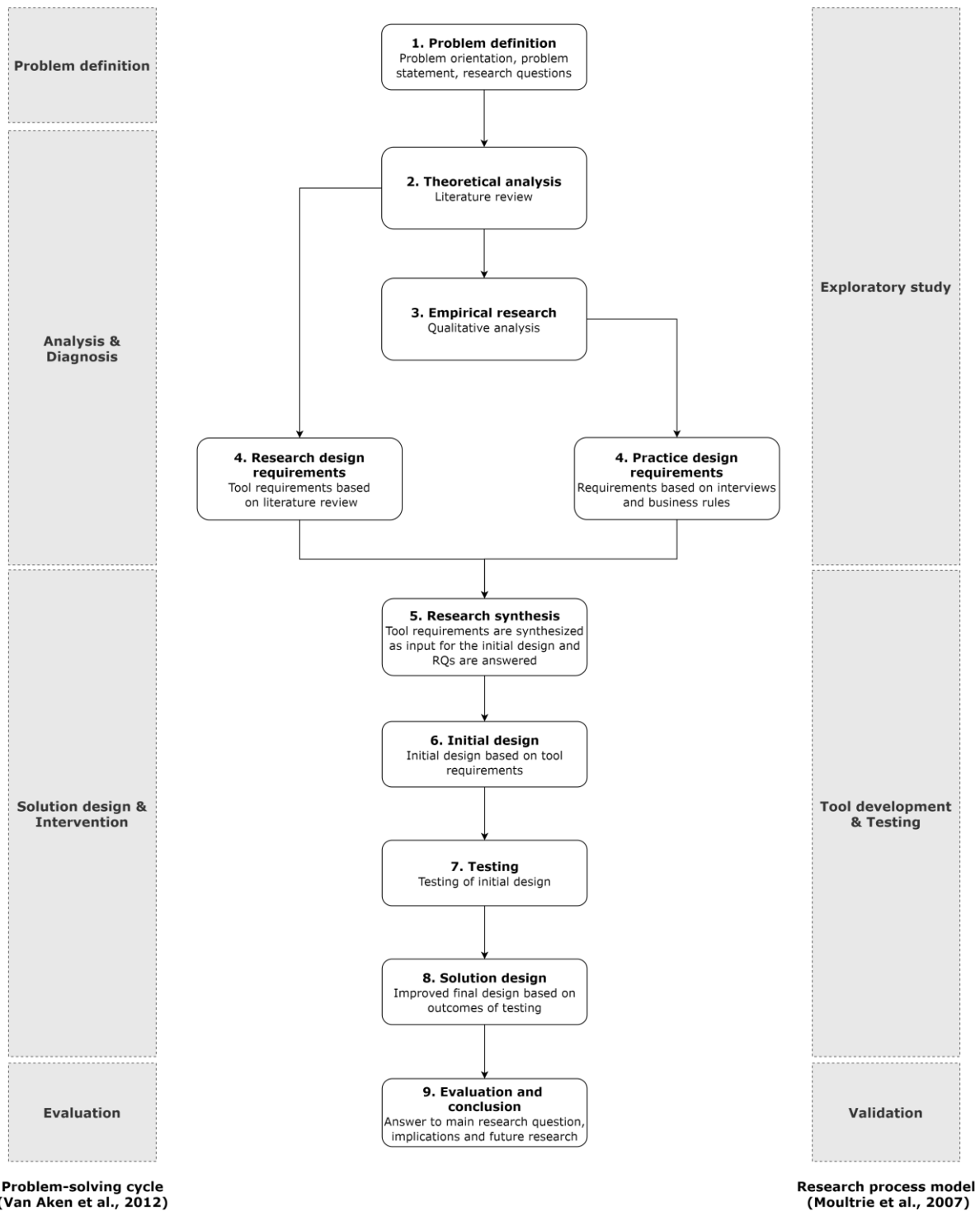


Figure 10 - Research design

The goal of this research is to design a tool, based on scientific and practical knowledge, that is used for monitoring the online content quality of PDPs. The first step in the research process is to have a problem intake and orientation process which is regarded as the problem definition (Van Aken et al., 2007). The problem definition consists of the problem orientation, the problem statement and the different sub-research questions that need to be answered to support in answering the main research

question. In the introduction the problem definition is stated. The next steps in the research design are the theoretical analysis and the empirical research which serve as input for the determination of design requirements for the tool. Besides serving as input for the design requirements, the theoretical analysis also serves as a theoretical framework to support empirical research and can be used as an extra source of evidence on causal relationships. The empirical research, supported by the theoretical analysis, is needed for the validation of the business problem and specifying its characteristics, exploring the causes of the business problem, validating the causes of the business problem and their relative importance and mapping the business process (Van Aken et al., 2007). In the research synthesis, the different requirements for the tool based on the theoretical analysis and empirical research are combined as input for the initial design of the tool. Testing is done to gain feedback and to validate the initial design to further improve and optimize the tool into the final solution design. The evaluation and conclusions are the last step in the research design and in this part answer to the main research question is given and the practical implications, limitations and future research directions are presented.

3.2. Materials and data collection

Literature used in this research are, in most cases, found via Google Scholar that linked to different scientific databases (e.g. ProQuest, JSTOR and Elsevier) where access via the TU/e was gained. For the problem definition and the theoretical analysis, different search strings were used to get relevant articles. The scope of the theoretical analysis was set to gather sources mostly in the field of online marketing, data management and information systems design. The relevance of the articles for this research had a higher priority than the impact factor of the journal due to the immature research field of the topic. The snowball method by Wohlin (2014) is used to look for citations and references of the used articles and to search for additional articles. For additional information on specific subjects (e.g., internal presentations by online retailers), the internal database of Signify was also consulted. To store and cite the articles that are used throughout this research, the reference manager Mendeley was used. All interviews for the empirical research and testing were conducted online via Microsoft Teams and recorded for analysis afterwards. Based on the problem definition, the data needed for this project mainly consists of PDP data from the scraping software. For every PDP, data is collected about the different PDP elements that are chosen to be important to determine the PDP quality. This data comes in raw format and needs to be converted to useful insights (the purpose of the tool). This data is available through a portal of the scraping software and can be accessed at any time. Furthermore, data on the products (e.g. product portfolio per retailer and images- and video file location) and or business rules are gathered from internal databases at Signify and access to this data is also available at any time. For designing the monitoring tool, Microsoft Excel was used for practical reasons.

3.3. Reliability and validity

To ensure that the research is valid and reliable, different methods were used. Reliability refers to the consistency of the operations of the research, such that the data collection procedures can be repeated with the same results. The goal of reliability is to minimize the bias and errors of the study (Sekaran & Bougie, 2016; Yin, 2003). To minimize the bias, semi-structured interviews were conducted and follow a funneling approach where the initial questions are very broad and gradually narrowing the focus to more specific themes (Sekaran & Bougie, 2016). In Appendix C the interview format is shown.

Validity refers to the extent to which the research results accurately represent the collected data and can be generalized to other domains (Sekaran & Bougie, 2016; Yin, 2011). The research was validated through the multi-methodological approach of the study through literature review, collection of qualitative data (empirical analysis) and testing the solution design for validation. Through triangulation, by using different information sources such as scientific articles, internal documents and presentations, interviews with experts, observations (through black box testing) and testing the tool in practice, the validity of this research was improved. Furthermore, the iterative method of designing, reviewing, and modifying also enhanced the validity. In order to verify that the statements by the participants during the interviews were correct, the results were checked with the participants to prevent false or unintended outcomes. The generalizability of designed monitoring tool in this research is constrained to the departments who deal with online retailers within Signify since the tool is tailor made for the internal business processes and rules for Signify. However, the PDP elements in general that are monitored will be about the same for other companies or industries that sell products through online retailers.

3.4. Procedure

To give a more detailed overview of the procedure of designing the monitoring tool, the process is divided in three phases, as shown in Figure 10. Phase 1 (analysis & diagnosis) consists of scientific- and practice-based research to answer the sub-research questions and to determine the design requirements for the initial tool design. In phase 2 (tool design), the tool is designed based on these design requirements and answers to the research questions. In phase 3 (testing & validation) the tool is tested and validated on its usability, utility, and output.

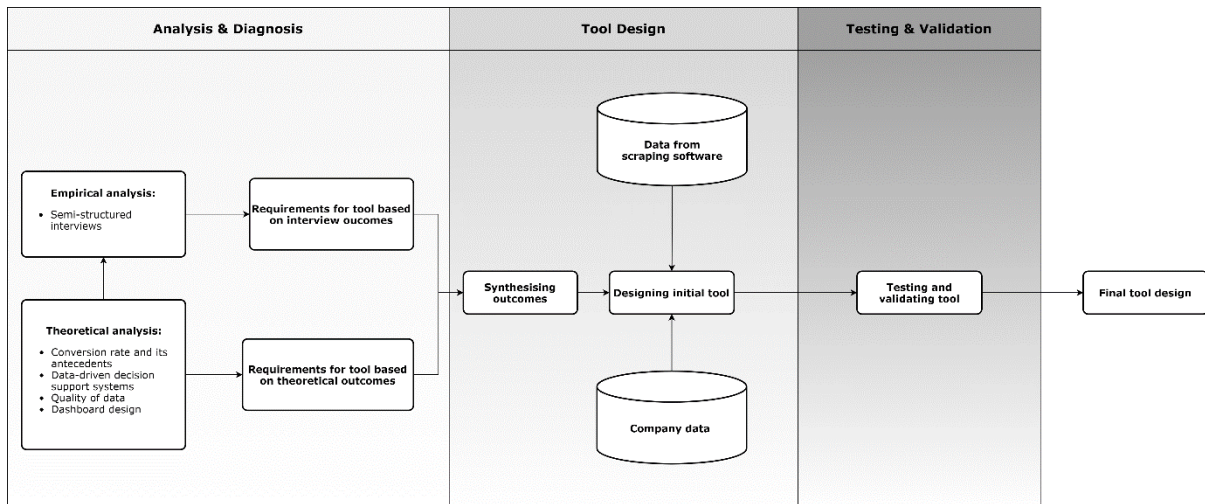


Figure 11 - Design procedure

3.4.1. Analysis & Diagnosis (phase 1)

To gain insights into the current way of working and the input and needs for the monitoring tool, semi-structured interviews were conducted with six experts from Signify in the field of sales and marketing. With these insights the design requirements were determined. Since the goal of the interviews is exploratory (gaining insights in the current way of working and the needs of the stakeholders for the tool), semi-structured interviews were conducted to determine the requirements for the tool because this method of interviewing fits best for this type of research (Sekaran & Bougie, 2016; Yin, 2011). The exploratory interviews were conducted online via Microsoft Teams and lasted around 30 minutes each. The six experts will be the main users of the tool and are therefore chosen to be the participants of this research. Since the interviews have an exploratory research purpose, the exact sample size was not specified a priori, but could be changed during the research where the interpretation of the researcher determines if the information gathered from the number of participants is sufficient and saturated enough to have a good understanding of the knowledge that is yet unknown (Sim et al., 2018).

The interview format, as can be seen in Appendix C, follows a funneling technique to minimize the bias of the questions by starting the questionnaire with general questions (e.g. questions about the role and work experience) followed by more specific questions regarding the definition and importance of content quality, the current method managing content quality and questions about the tool itself (e.g. what requirements the tool needs) in an unbiased way. In the semi-structured interviews, the specific questions are used to ensure that the interview covers the necessary areas and ask the questions in a similar way in every interview. However, there is also room for the interviewee to elaborate or follow up on their own statements and thoughts (Blumberg et al., 2011). After the sixth interview the researcher noticed that theoretical saturation was reached regarding the

different questions and subjects because no new information and insights were gained (Sekaran & Bougie, 2016).

3.4.1.1. *Current way of managing online content (RQ1)*

To understand the current issues of managing online content on PDPs by the sales and marketing department, the current way of working and the associated problems that arise needed to be analyzed. To determine the current way of working, interview questions regarding the process of delivering content to retailers and the causes of insufficient content quality on PDPs were asked.

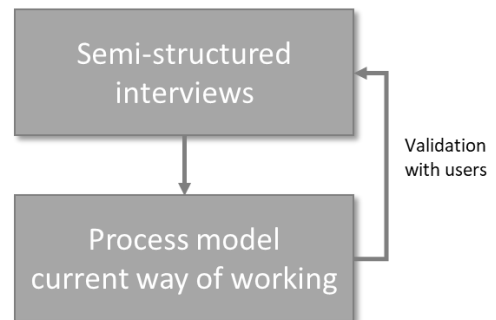


Figure 12 - Approach for RQ1

Furthermore, the different PDP elements that the employees at Signify have direct influence on were also obtained during the interview. The interview was semi-structured so that the participants can elaborate on the answers. Based on the information obtained during the interviews regarding this subject, a process model was created. This process model was validated with the users to confirm that it was an accurate representation of the current way of working. In Figure 11, the approach for answering RQ1 is given.

3.4.1.2. *Determinants of PDP content quality (RQ2)*

To determine which PDP elements are the determinants of the PDP content quality that affect the conversion rate and the sales velocity, a theoretical analysis on the factors that influence this was done. The next step was to check for every factor if it is relevant to measure this for the tool and if it is possible to get the data for these factors. The relevancy and possibility to measure the factors identified in literature were validated through the interviews with the sales and marketing experts. The outcomes of this were used to determine the relevant PDP elements to implement in the tool. In Figure 12, the approach for answering RQ2 is given.

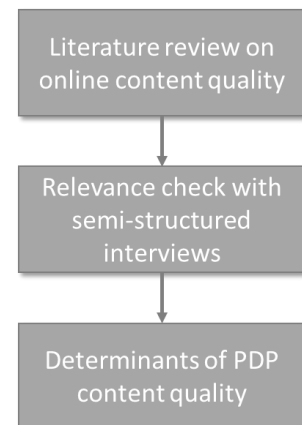


Figure 13 - Approach for RQ2

3.4.1.3. Relevant data quality dimensions (RQ3)

The quality of the data that is used as input determines the trustworthiness and reliability of the tool. Because the decisions that will be taken by the users of the tool are based on the outcomes that the tool presents, it is important to have good data quality. In order to check the data quality, different data quality dimensions are identified in literature (Wang & Strong, 1996) to determine the data quality of a given dataset. As there is a difference in relevancy of these data dimensions for every application, depending on the dataset and purpose of the tool, interviews with the users are held to capture the relevant data quality dimensions for the monitoring tool. In Figure 13, the approach for answering RQ3 is given.

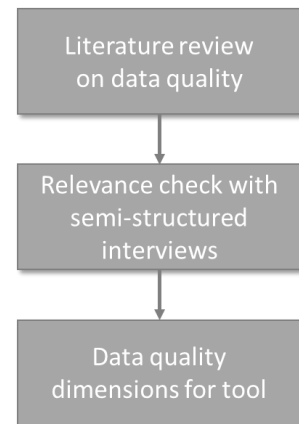


Figure 14 - Approach for RQ3

3.4.1.4. PDP content quality assessment (RQ4)

The way of assessing the content quality of a PDP in the tool determines how the content quality at each PDP is calculated and displayed. The outcomes of these calculations represent the content quality score for different PDP elements where the calculation is based on business rules regarding content quality at Signify. With the implementation of these business rules, different formulas for calculating the content quality for each PDP element were determined and the overall content quality could be assessed. During the testing of the initial design, the content quality assessment was validated. In Figure 14, the approach for answering RQ4 is given.

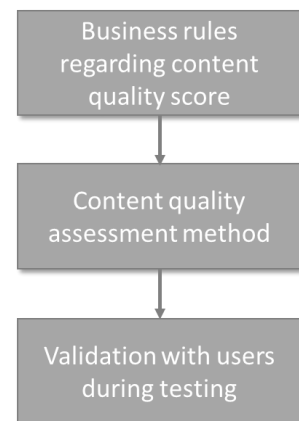


Figure 15 - Approach for RQ4

3.4.1.5. Tool interface design (RQ5)

The interface of the tool is important for ordering the different types of KPIs that are present in the tool. To determine how the interface and layout of the tool should be developed, literature on the design of dashboards was used. The tool design depends on the purpose of tool and the needs of the user. In the literature review on dashboard design, data selection methods, visualization techniques and other dashboard characteristics are presented to implement in the design of the monitoring tool. After implementing these characteristics, during the testing of the initial design, the interface of the tool is validated by the users. In Figure 15, the approach for answering RQ5 is given.

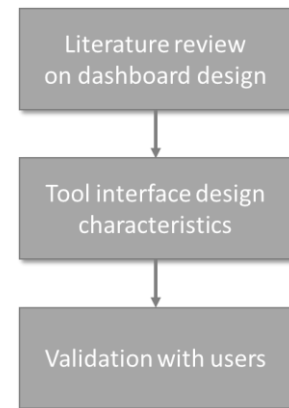


Figure 16 - Approach for RQ5

3.4.2. Tool design (phase 2)

In phase 2, the requirements that were constructed from both empirical research and theoretical analysis are used as input for the design of the monitoring tool. The tool requirements were divided into four categories following the design theory: functional requirements, user requirements, boundary requirements and design restrictions (Van Aken et al., 2007). These requirements are formed to structure the initial design. The development of the initial tool design is an iterative process in which changes are constantly reviewed, modified and applied. Input for designing the tool were the design requirements, scraped PDP data and company data on the different products. These three elements together form building blocks for designing the monitoring tool.

3.4.3. User testing & Validation (phase 3)

After developing the initial design, the tool was tested and validated for adoption through five participants (four key account managers and one channel marketer) that were also involved in the semi-structured interviews. The goal is to test if the initial design does what it is supposed to do, if it is easy to use and if the desired output is acquired. The initial tool design was presented to the participants that used the tool for a couple of days. From the outcomes of the testing, improvements are identified and implemented into the final design. The participants were asked to use the initial tool through black box testing, where the compliance of the tool was evaluated without knowing the internal workings of the tool. This method of testing leads to reduced developer-bias since the participants of the test have not been involved in the tool's technical development. The goal of black box testing is to review and test the functionalities of the initial design of the tool. The participants gave feedback on the working of the tool during the interview.

After using the tool, the tool was evaluated based on three different criteria by the participants. These criteria are based on action research used by Moultrie et al. (2007) for the evaluation of a similar tool used for auditing SMEs. The criteria addressed the usability, utility and output of the tool. The goal is to evaluate on the initial design for the three evaluation criteria. The interviews were held separately with each participant and lasted for 45 minutes on average.

3.4.3.1. Usability

When a product or service has a high usability, it is described as clear, unambiguous, and can be followed as described without clarification. This includes establishing errors of omission or commission, as well as ensuring that the tool was appropriately structured and presented. Furthermore, it describes the ease of use and learnability of, in this case, a software tool. (Cáñez et al., 2000; Maslen & Lewis, 1994; Platts, 1993). To assess the usability of the tool, the System Usability Scale (SUS) was used. The SUS method is initially developed by Brooke (1996) and further modified by Bangor et al. (2008). This survey method allows the practitioner to quickly and easily assess the usability of a given product or service. This method is often used when assessing an interface technology, like the monitoring tool. It consists of 10 questions with a 5-point Likert scale where the answers range from “strongly disagree” to “strongly agree”. The final score per user ranges from 0-100, where higher scores indicate better usability. In Appendix J an overview of the survey and the calculation method is shown. The SUS score is not used in isolation to make absolute judgements about the “goodness” of the monitoring tool, but it serves as a useful metric for overall product usability (Bangor et al., 2008). The rule of thumb is that a SUS score above 68 (50th percentile) is the least score for the tool to be passable on usability. A score above 90 is defined as truly superior.

3.4.3.2. Utility

To assess whether the monitoring tool achieved the intended objectives, from both the company’s- and the researcher’s perspective, and that the outputs were a result of using the monitoring tool, the utility of the tool was tested. This was done via a short semi-structured interview with the participants where they had the possibility to openly express their opinion on the utility of the tool and if the tool did what it is intended to do.

3.4.3.3. Output

To establish whether the monitoring tool is delivering the intended output, the participants were asked to write down which actions to improve the content quality were taken by using the tool. The results from these actions are explicit and implicit outputs from using the tool (Eckert et al., 2003; Maslen and Lewis, 1994). The actions (e.g. changing product title, adding images, adding product video) are taken by the participant itself or an assistant key account manager (AKAM). When the

corresponding actions had been taken, changes in the content quality were monitored by comparing the new content score for the improved PDPs with the initial content score for the same PDP before the improvement. The change in the content score was a direct result of the tool.

3.5. Participants

In this research a total of six experts from Signify participated with the development of the monitoring tool. The participants were formally involved within the semi-structured interviews and the testing and validating but also gave informal feedback during the design phase. The six experts were selected because of their knowledge and experience in the field of marketing and sales and the fact that they were most likely the end users of the tool and involving the users is an important part in the acceptance of the tool (Morgan & Inks, 2001; Speier & Venkatesh, 2002). In Table 3 an overview of the participants is given per phase. The first phase consisted of the scientific- and practical knowledge phase in which the collection of qualitative data was used for determination for the design requirements. In the second phase, the testing and validation of the monitoring tool were conducted with the participants.

Table 3 - Overview participants

Participant role	Information	Data collection type phase 1	Data collection type phase 2
Key Account Manager Online #1	>3 years experience as account manager (8 months at Signify)	Semi-structured interview	Black box testing and semi-structured interview
Key Account Manager Online #2	>5 years experience as account manager (two years at Signify)	Semi-structured interview	Black box testing and semi-structured interview
Key Account Manager Online #3	6 months experience as account manager at Signify	Semi-structured interview	Black box testing and semi-structured interview
Key Account Manager ERT-channel #4	2 years experience as account manager at Signify	Semi-structured interview	Black box testing and semi-structured interview
Key Account Manager ERT-channel #5	1,5 years experience as account manager at Signify	Semi-structured interview	-
Channel Marketeer Online and ERT-channel	>5 years experience as channel marketeer (1,5 years at Signify)	Semi-structured interview	Black box testing and semi-structured interview

4. Analysis & Diagnosis

In this chapter, the outcomes from the empirical research are discussed and the design requirements are identified. The expert data analysis describes the outcomes of the semi-structured interviews with sales- and marketing experts. These outcomes, together with the outcomes of the theoretical analysis, are used in order to answer RQ1 to RQ4. Finally, based on these answers, the different design requirements are presented. The design requirements consist out of the functional requirements, user requirements, boundary conditions and design restrictions (Van Aken et al., 2007).

4.1. Expert data analysis

In this section, the qualitative data that was collected through the semi-structured interviews is analyzed and discussed. The outcomes of the interviews, together with the outcomes of the literature review, serve as input for determining the design requirements of the monitoring tool. This section is split into three parts: current method of managing online content, the value of online content quality, and the requirements for the monitoring tool.

4.1.1. Current method of managing online content (RQ1)

The current method of managing and delivering content at online retailers is not a standardized and satisfactory process in the eyes of the participants. An interviewee (KAM #4) said that “it is a difficult process that is different for every retailer, it is also a manual process which makes it more likely that errors are being made by delivering the content (i.e. missing images, missing product descriptions)”. Another interviewee (KAM #1) mentioned that “often there is no focus on delivering the right information to the retailers and the focus of the retailers on putting the right or all delivered content online is also not always present”. Additionally, a participant (KAM #2) mentioned that for online retailers that have a marketplace (i.e. Amazon and bol.com), the situation of managing content has an extra difficulty because “third party vendors that sell our products via a platform like bol.com can change the online content of these products via a vendor portal. This makes it possible for these external vendors to change the content that we initially delivered to bol.com as the manufacturer of these products without our consent”. For the employees of Signify it is not possible and sustainable to check for every product if the content has been changed by a third-party vendor on a regular basis manually since this would cost a lot of time “we cannot manually check all these PDPs if a third party seller changed content for our products because this would be way too time consuming”. The elements on the PDP that are manageable are for most retailers the more or less the same, as one interviewee (KAM #1) mentioned “the product title, product images and videos, product description and the specification table are the elements that we have direct influence on and it is our job to deliver the content for these elements in the right format to the retailer”. Lastly, it is currently not possible

to benchmark or test the content quality and compare it to other retailers, one interviewee (KAM #3) mentioned: “It is not possible to monitor and benchmark the content quality of my accounts and compare this to other retailers to see how we are doing. For me the possibility to do this would be very nice”. The current way of managing content is presented in a flowchart in Figure 16. Since the exact process of delivering content is different for every online retailer, a generalized model of managing the content quality is constructed.

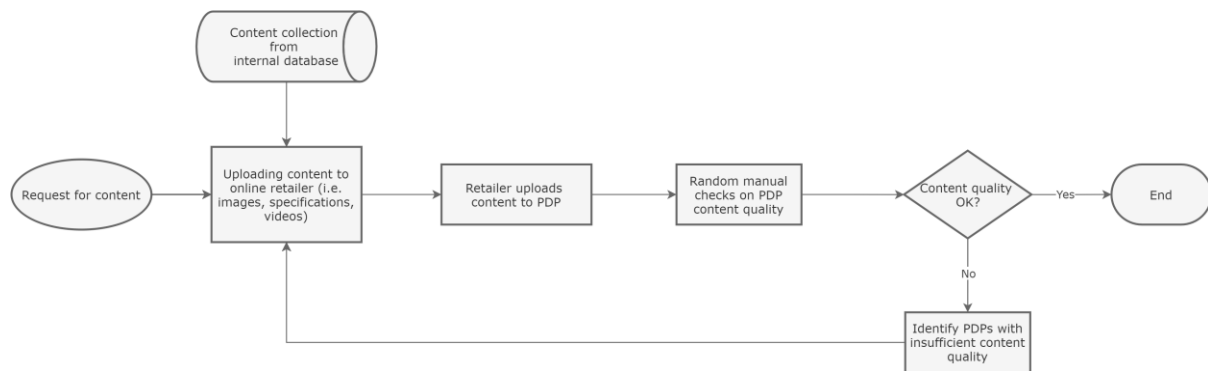


Figure 17 - Current general way of managing content quality

4.1.2. Value of online content quality

To get a better impression about the importance of online content quality and managing this, three questions about the value of content quality for Signify were asked. The answers were slightly different between the experts but came down to the same thing. One of the interviewees (KAM #1) said that, in line with the literature, “online content must inform and convince the consumer as good as possible because the consumer cannot see or feel the product in real life, for this reason improving on content quality will improve the chances that a consumer is inclined to buy the product on the PDP. It has a key role in the customer journey”. This statement was also affirmed by the other participants. Another interviewee (KAM #2) also mentioned that “a PDP with its content quality can distinguish itself from the competition by offering more and better information on the product”. For this reason, it is important for Signify to deliver the best content possible in order to remain competitive. When asked what the goal is when optimizing the online content quality all experts were unanimous about the main goal, for example one interviewee said (Channel Marketeer) “the goal of improving the online content quality is to improve the conversion rate since, normally speaking, a higher conversion rate means more sales”. Furthermore, it was also mentioned by two participants that better content quality can also reduce the number of returns by customers, it was said that (KAM #1) “good content quality will also lead to fewer returns when customers are informed better about the product. For example, when different versions of one product are sold by a retailer and the consumer, by accident, buys the wrong version of the product. When the consumer is informed better, some of the returns

could have been avoided". Because every retailer has its own interface of a PDP and own set of PDP elements, content quality has its own meaning and value for every retailer. An interviewee (KAM #3) mentioned that "not every retailer that falls under my responsibility has the ability to write reviews or a show a specification table, other accounts however are more focused on perfecting the content quality by offering rich content on the PDP". For this reason, it is also very important to know for every retailer what the possibilities are to improve the content for since not every type on content can be present on the PDP.

4.1.3. Requirements for the monitoring tool

The experts value the idea of a tool to monitor the content quality across different retailers and think that on multiple levels a monitoring tool can be very helpful for their work as, in this case, account manager or channel marketer. For the added value of the tool, saving time is mentioned as most important factor for using the tool by the interviewees "for me the main advantage of a monitoring tool would be that you can instantly see how your retailers are doing in terms of content quality. Instead of manually checking PDPs, a tool can give these insights immediately and in a structured way. This will save a lot of time that I can spend on other things". The different types of elements that the interviewees want to have monitored within the tool are in line with the elements that they have direct influence on (i.e. product images and videos, product title, product description and the specification table). Multiple participants mentioned that within Signify, contractual agreements are present with retailers regarding the content quality on the PDPs, as one of the participants said (KAM #3) "we have contractual agreements with retailers where we should check if retailers meet the requirements we set for our PDPs. If everything is alright, the retailer obtains a discount on the purchase price. Unfortunately, it is currently impossible for us to check whether the retailer meets these requirements. These agreements partly consist of the presence of different PDP elements". Furthermore, two interviewees also mention that information and insights on different PDP elements that they do not directly have influence on are also sources of valuable information to make analyses with. An interviewee (KAM #2) said that "besides the directly manageable PDP content quality elements, it would also be nice for internal analyses to have insights in other PDP elements such as the availability, price and the reviews of a product which are also present on the PDP". Ease of use for the tool is the most mentioned requirement by the interviewees, this is in line with the theory about dashboard design (Janes et al., 2013). One interviewee said that "the tool has to be user friendly in the sense that I can easily find the things I want to see without having to do a lot of manual actions. If I have to do too much for the data I want, I probably will not use the tool since it costs too much time and energy". Besides the ease of use, also a user-friendly interface and relevant data displays are mentioned as requirements for the tool. Furthermore, four participants mention that the quality of

data is the a very important requirement that needs to be assured in order to rely on the tool and use it. An interviewee (KAM #1) mentioned that “good data quality is crucial for the reliability of the tool. If the data in the tool is false or incomplete, analyses could be wrong and could harm the company”. Data accuracy, data completeness, and timeliness data is mentioned multiple times as important factors that determine the quality and usefulness of the tool. As one participant (KAM #3) said “the data in tool needs to be up to date in order to make quick actions”. This statement is also in line with literature regarding data quality and the timeliness data dimension (Wang & Strong, 1996).

4.1.4. Conclusion

Following the outcomes of the expert analysis, the necessity of having a tool that is able to monitor the content quality on PDPs is clear. The semi-structured interviews showed that people responsible for the content quality at online retailers lack the ability to monitor and manage this, mainly because it is currently not possible to have quick and clear insights in the content quality. A tool that is able to convert raw scraped data from PDPs across different retailers into useful insights is something that will add value to the company by giving the users that data they need to be able to improve the content and therefore the conversion rate.

4.2. Relevant PDP elements (RQ2)

From the theoretical- and the expert analysis, the relevant PDP elements to measure are obtained. The identified PDP in literature that determine the content quality of a PDP are in line with the outcomes of the expert analysis. However, from the interviews with the sales and marketing employees it also became evident that other PDP elements, that are not directly linked to the content quality, are also desired in the tool. For this reason, the PDP elements are categorized in two different types to indicate the difference between a PDP element that defines the content quality and other PDP elements serving a different purpose. For assessing the content quality, eight PDP elements are identified. Besides the content quality elements, three other PDP elements are identified to be useful. The relevant PDP elements for the monitoring tool are presented in Table 4.

Table 4 - Relevant PDP elements for the tool

PDP element	Category
Image	Content quality
Specification table	Content quality
Product description	Content quality
Product title	Content quality
Brand name	Content quality

Video	Content quality
Rich content	Content quality
Review	Content quality
Buybox seller	Other
Price	Other
Availability	Other

4.3. Relevant data quality dimensions (RQ3)

For the determination of the relevant data quality dimensions, the data quality framework by Wang & Strong (1996) is used as the basis to determine which of the dimensions of are relevant for the tool. The data dimensions that are specifically mentioned as very relevant for the tool by the interviewees are data accuracy, the trustworthiness of the data (i.e. believability), data completeness and the timeliness of data. Furthermore, following the participants that mention the importance of the ease of use of the tool, appropriate amount of data, data relevancy, ease of understanding and data interpretability are also data quality dimensions that are relevant for the tool (Wang & Strong, 1996). The importance of data relevancy and value-added dimensions were covered in the determination of relevant PDP elements and are therefore also relevant data quality dimensions. Lastly, regarding the accessibility of the data, it is important for the users that the tool and the data for the tool is easily retrieved. An overview of the relevant data quality dimensions for the tool is presented in Table 5.

Table 5 - Relevant data quality dimensions for the tool

Data quality dimension	Category
Accuracy	Intrinsic data quality
Believability	Intrinsic data quality
Value-added	Contextual data quality
Timeliness	Contextual data quality
Completeness	Contextual data quality
Appropriate amount of data	Contextual data quality
Relevancy	Contextual data quality
Ease of understanding	Representational data quality
Interpretability	Representational data quality
Accessibility	Accessible data quality

4.4. PDP content quality assessment (RQ4)

For the assessment of the content quality, business rules regarding content quality at Signify were used to calculate the content quality score. Based on contractual agreements with retailers regarding the content on PDPs, a method to calculate the content quality score per retailer was determined. Since there is a distinction between basic- and extended PDP elements in the contractual agreements, a distinction in the calculation of the content score was also made. For the basic content score, the presence of basic PDP elements is determined. For the extended content score, the PDP elements that are less common at retailers are measured. The content score represents the percentage of the PDP elements that is present dependent on the chosen product categories for a certain retailer. The following formulas were used to calculate both content scores:

$$\text{Basic content score} = \frac{\% \geq 5 \text{ images present} + \% \text{ specs table filled} + \% \text{ product description present} + \% \text{ product name present} + \% \text{ brand name present} + \% \text{ brand name present in product title}}{6}$$

$$\text{Extended content score} = \frac{\% \text{ rich content present} + \% \text{ product review present} + \% \text{ video present}}{3}$$

In the contractual agreements with retailers, no distinction is made in the importance between different PDP elements. Furthermore, in scientific literature no explicit distinction was found to rank or classify the importance of each of the PDP elements. For this reason, equal weights have been assigned to all variables for the basic- and extended content score.

Furthermore, threshold values are used in combination with a color-coding scheme to make a distinction between the different content scores more visible. Three colors (red, yellow, and green) are used to represent the importance of improving the content quality for selected KPIs. Since there are no business rules on the determination of the threshold values for the different colors, the participants were asked which colors belonged to which value ranges in their opinion. From these answers the threshold values shown in Table 6 were determined and used within the tool.

Table 6 - Threshold values for color coding KPIs

Color	Range of score	Meaning
Red	0% - 59,99%	High urgency for improving the content quality
Yellow	60,00% - 79,99%	Neutral urgency for improving the content quality
Green	80% - 100%	Low urgency for improving the content quality

In the future these threshold values could be changed depended on the development of the content quality across the different retailers. If the mean content quality scores are rising, it might be useful to increase the threshold values to give additional incentives to the users to further improve on the content quality since it will be harder to get a “green score” in this scenario.

4.5. Design requirements

To synthesize the outcomes of the theoretical- and expert analysis, design requirements are used to evaluate possible solutions against the specifications. This method is based on the design theory and part of the solution design phase in the problem solving cycle (Van Aken et al., 2007). The functional requirements are the core of the specification in the of performance demands on the object that is designed, user requirements are specific requirements from the viewpoint of the user, boundary conditions must be met unconditionally and the design requirements define the preferred solution space (Van Aken et al., 2007). For each requirement it is indicated between brackets whether it originated from literature, from the company or both. The different requirements for the tool are stated below.

Functional requirements

1. The tool should support Signify in monitoring and managing the online content quality at different retailers (company requirement).
2. The tool will have a dashboard with different KPIs and charts that are important to monitor and manage the online content quality (literature and company requirement).
3. The tool should provide content quality information on both retailer and product level (company requirement).
4. The tool should provide a content score to assess the content quality based on business rules (company requirement).
5. The tool should be able to let the user of the tool make their own analysis and allow the user to drill-down within the tool (literature and company requirement).

User requirements

6. The tool should be user friendly. This means that it must be easy to navigate between different tabs and simple to obtain the results the user wants to see (literature and company requirement).
7. The KPIs and charts within the tool should be easy to understand. This means that KPIs and charts should be self-evident, or an explanation should be present (literature and company requirement).

8. The tool should be able to show results that are specifically relevant for different users (literature and company requirement).
9. The purpose of tool should be clear for the user (literature and company requirement).

Boundary conditions

10. The tool should comply with present legal requirements (company requirement).
11. The tool is for internal use at Signify (company requirement).
12. All data that the tool uses should be accurate, timely and complete (literature and company requirement).

Design restrictions

13. The tool must be designed within Microsoft Excel (company requirement).

5. Solution design

In this chapter the final solution design of the monitoring tool is presented. The first step was to design the initial design through an iterative design process and based on the design requirements identified in Chapter 4. Furthermore, answer to RQ5 is given and the initial tool is tested and evaluated on three criteria and the design requirements in order to present the final solution design.

5.1. Initial design monitoring tool

In this section the initial design of the monitoring tool is described and presented. First, the development process of the tool is presented, followed by an in-depth explanation of the tool with the integration of both literature and the outcomes of the semi-structured interview into the design.

5.1.1. New content managing process

The development of the monitoring tool changes and improves the current content management process that was identified during the expert analysis. With the ability to monitor the content quality via a tool instead of manually checking random PDPs, the overall content quality across the online retailers is expected to improve and will have an impact on the conversion rate and sales velocity. On a weekly basis, input data from the scraping software will be loaded into the tool to give the users insights into the different PDP elements that determine the content quality and the other PDP elements. The new and improved way of managing content after the implementation of the monitoring tool is shown in Figure 17.

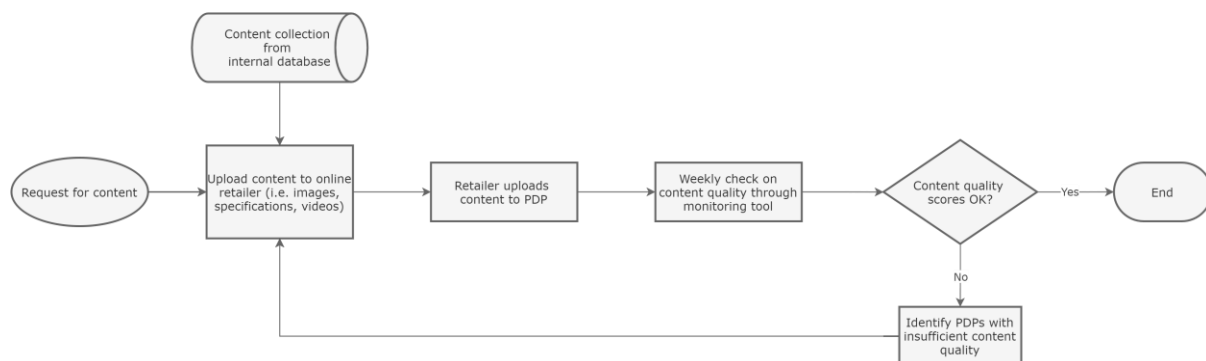


Figure 18 - New content managing process

5.1.2. Data collection

The first step is to determine which data is needed to be collected to serve the goal of the monitoring tool. To do this, the GQM model by Janes et al. (2013) was used. The GQM model gives a schematic overview of the different types of input data that were used in order to answer the questions to reach the goal of the tool, which is improving the monitoring ability of PDP elements. The input for the questions of the GQM model are extracted from the expert analysis. During the interviews, the users

mentioned the PDP elements they wanted to have insights to in order to improve their ability to manage the content quality and monitor other PDP elements. These elements are incorporated into six questions. To answer these questions, nine measures were identified which define the data that is needed to be collected to answer the questions. In Figure 18, the GQM model for the monitoring tool is shown with the nine measures on the bottom row which answer the six questions in order to reach the end goal of improving the monitoring ability of PDP elements.

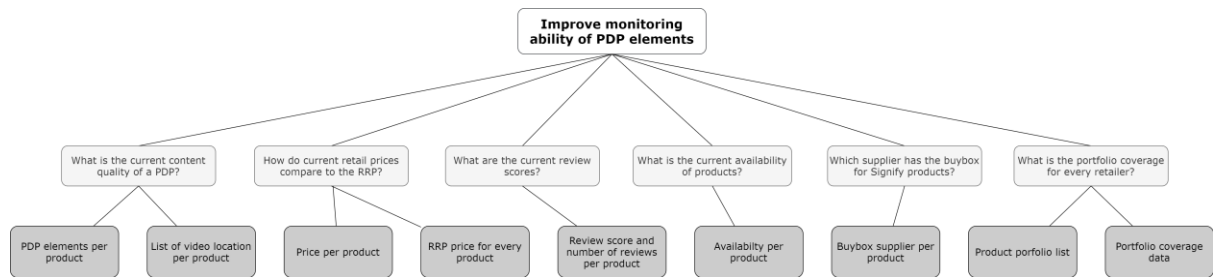


Figure 19 - GQM model monitoring tool

5.1.3. Tool architecture

The tool architecture shows the underlying data links between the different components of the tool that are created in order to present the data that the user needs to monitor and manage the online content quality. To give an overview on how the underlying data between the different components of are connected, the tool architecture is presented in Figure 19.

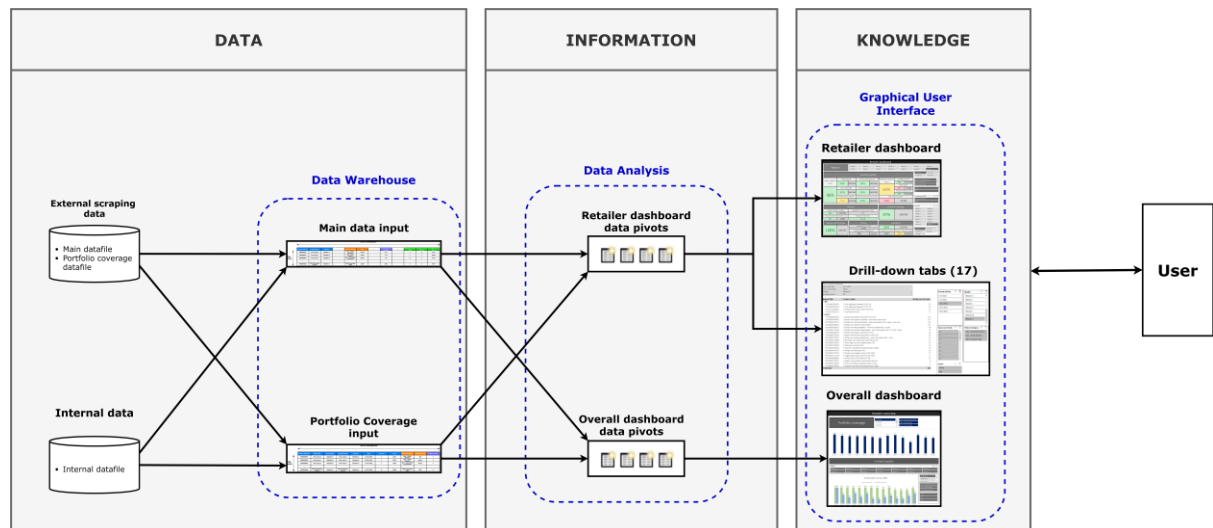


Figure 20 - Tool architecture

First, the external data from the scraping is stored into the Main data input tab and the Portfolio Coverage tab and linked with variables from the internal database. This two data tabs function as the data warehouse. Next, to present the data from the Main data input tab and the Portfolio Coverage input tab to the user of the tool, pivot tables for every KPI and chart are created which calculate and

display the data for the selected filters by the user. This is done in the data analysis. The last step is to show the results in graphical user interface. The user interacts with two different dashboards to show the relevant KPIs and charts it wants to see. Furthermore, drill-down tabs are created to allow the user to make more detailed analyses and present a list of the PDPs that do not have sufficient content quality. The three elements of the data-driven decision-making framework by Mandinach et al. (2006) are used to show the different stages regarding the continuum in which the data is transformed to information and ultimately to knowledge that can be used to make decisions (i.e. take actions). In the section below the three different stages are further elaborated.

5.1.3.1. Data sources

The tool uses two different data sources to get the data that is needed to assess the content quality and make analyses. These data sources consist of the external database in the form of the scraping software output and the internal database of Signify. The data from the scraping software comes in two different files: a main datafile with the variables regarding the content quality and other PDP elements and a data file regarding the portfolio coverage per retailer. It is a technical limitation of the scraping software that is delivered into two separate datafiles. The data from the scraping tool is stored in a comma-separated value (.csv) format. This file type can be imported into Microsoft Excel, in which the tool is developed. The data from the internal database was stored in a Microsoft Excel file (.xls format) and could be directly imported into the tool.

Scraping software

The data from the PDPs of different online retailers is being scraped by a web-based software tool that specializes in scraping different PDP elements. The software tool scrapes the data for the selected PDP elements. For the monitoring tool, the selected elements are based on the identified relevant PDP elements in the expert analysis. After selecting the PDP elements, the scraping software delivers data file with the PDP data for the selected retailers. This file is downloaded and stored to an internal folder after which it is imported to the monitoring tool. In Appendix F, an example of the data that comes from the scraping software is shown. This raw datafile has been converted from a comma-separated file to a file with columns to make it readable.

Internal datafile

The internal data file contains additional information to the scraped datafiles for more in-depth analyzations and filtering possibilities. The Retail Recommended Price (RRP) is added to let the user compare the current prices of retailers with the recommended selling price. Furthermore, the category of a product is added to be able to differentiate between different types of lamps (i.e. Hue - Luminaires, Hue - Home Systems and WiZ Connected). The product status is helpful to make a

distinction for products that are new (i.e. new product introduction), active and products that are soon to be phased out. Lastly, variables that state the video location and video name are added to the tool to inform the user where the video files for products without a video on the PDP can be found in the internal Signify database. The data variables for the internal datafile are shown in Table 7. For these variables, an overview and explanation of the data variables are shown in Appendix E.

Table 7 - Data variables internal datafile

Data variables internal datafile	
<i>Product EAN/UPC</i>	<i>Product Status</i>
<i>Product Name</i>	<i>Product Category</i>
<i>Brand Name</i>	<i>Video Location</i>
<i>Retail Recommended Price (RRP)</i>	<i>Video Title</i>
<i>Bundle Product</i>	

Main datafile

The main datafile from the scraping software consists of 23 different data variables that are used for the calculations of the different KPIs in the dashboard. Each data variable is placed in a column and for every PDP that is scraped the columns are filled with the corresponding, scraped value. The scraped data for one date for 12 retailers typically consist of around 3000 rows of data and around 70000 different values. The scraped data variables for the main datafile are shown in Table 8. In Appendix E, all data variables in the tool are presented including a description of the variable.

Table 8 - Data variables main datafile

Data variables main datafile (scraping software)		
<i>Product EAN/UPC</i>	<i>Product without any Reviews</i>	<i>Specs Table present</i>
<i>Product Name</i>	<i>Review Count</i>	<i>Product Descr present</i>
<i>Retailer</i>	<i>Review Score not adjusted</i>	<i>Product Title</i>
<i>Seller</i>	<i>Image Count</i>	<i>Brand</i>
<i>Download Date</i>	<i>Video Count</i>	<i>Rich Content present</i>
<i>Product Page URL</i>	<i>Main Category</i>	<i>Retailer product ID</i>
<i>In Stock</i>	<i>Sell Price incorrect format</i>	<i>SL ID</i>
<i>Days out of Stock</i>	<i>MPN</i>	

The data from the main datafile is used as the basis for the input for the calculations and analyses that are shown in the dashboard. In the *Main data input* tab in the tool, the relevant data values from the internal datafile (*Retail Recommended Price (RRP)*, *Product Status*, *Product Category*, *Bundle Product*, *Video Location* and *Video Title*) are added to the data from the main datafile by linking the EAN numbers for the scraped PDPs to the EAN numbers in the internal datafile. The EAN number for every product is unique and can therefore be used as an identifier for that specific product. Besides the six

added variables from the internal datafile, also 30 calculations for analysis purposes per product are made in the *Main data input* tab. This means that to the existing 23 variables in the main datafile, an additional 36 variables are added through calculations and added data from the internal datafile. This makes a total 59 variables that are used for the analyses for the content quality and the other PDP elements. The data in *Main data input* tab will continuously grow since all data will be stored for every time that the tool is ran by the user. In Figure 20, the schematic overview of the *Main data input* tab is shown. For readability reasons, a selection of the total of 59 data variables are shown. The full list of data variables and calculations are shown in Appendix E. The colors of the columns indicate the type of the variable: scraping software (blue), Signify internal (orange), general calculation (purple) and content score calculation (green).

DATA VARIABLES

Product EAN/UPC	Product Name	Retailer	...	Product Category	RRP	...	Percentage Price Deviation	...	[Bas] Specs table filled	[Ext] Rich content percent	Extended Content Score
000000001	Hue Lamp X	Retailer A		Hue - Home Systems	44,99		5%		1	0	67%
000000002	Hue Lamp Y	Retailer B		Hue - Home Systems	35,99		-5%		1	1	100%
000000003	Hue Lamp Z	Retailer B		Hue - Connected Luminaires	69,99		7%		0	1	67%
...											
000003000	WIZ Connected Lamp X	Retailer X		WIZ Connected Light	12,99		10%		1	1	33%

PDP DATA

Figure 21 - Main data input tab

Portfolio coverage datafile

The portfolio coverage datafile is build up in the same way as the main datafile. This datafile however only has eight data variables since the only purpose of this datafile is to get information about the online presence of a product that is in the product portfolio of the retailer. The scraped data for this datafile has the same number of rows as the main datafile for each date (i.e. around 3000) and consists of around 25000 different values. The scraped data variables for the portfolio coverage datafile are shown in Table 9. An overview and explanation of the data variables and calculations is shown in Appendix E.

Table 9 - Data variables portfolio coverage datafile

Data variables portfolio coverage datafile (scraping software)	
<i>Product EAN/UPC</i>	<i>Retailer</i>
<i>MPN Code</i>	<i>Date</i>
<i>Brand Name</i>	<i>Covered</i>
<i>Product Name</i>	<i>SL ID</i>

For the data in the portfolio coverage datafile, a different tab is used to store the data. This is done in the *Portfolio Coverage input* tab. The way in which the data is organized is the same as for the *Main data input* tab. The scraped data is used as the basis and data from the internal datafile is used to add relevant variables (*Product Status* and *Product Category*). To calculate the portfolio coverage, a *Helper*

Column is added where all values are equal to 1. In Figure 21, the schematic overview of the *Portfolio Coverage input* tab is shown.

Product EAN/UPC	MPN Code	Brand Name	Product Name	Retailer	Date	Covered	SL ID	Product Category	Product Status	Helper Column
000000001	Hue Lamp X	Retailer A	Hue Lamp X	Retailer A	11-04-2021	1	1001	Hue - Home Systems	Old	1
000000002	Hue Lamp Y	Retailer B	Hue Lamp Y	Retailer B	11-04-2021	1	1002	Hue - Home Systems	Active	1
000000003	Hue Lamp Z	Retailer B	Hue Lamp Z	Retailer B	11-04-2021	1	1003	Hue - Connected Luminaires	Active	1
...										
000003000	WIZ Connected Lamp X	Retailer X	WIZ Connected Lamp X	Retailer X	11-04-2021	0	4000	WIZ Connected Light	NPI	1

Figure 22 - *Portfolio Coverage input* tab

5.1.3.2. Data analysis

With the data being collected and organized, the next step is to analyze it. The analyses are done by using pivot tables. Pivot tables are used to make it easy and simple for the user to compare and filter data with just a few clicks. With the help of a pivot table different retailers and product categories can be selected according to the needs of the user for a chosen PDP element. For the tool, two different dashboards are made: a retailer dashboard and an overall dashboard. The retailer dashboard shows the user the KPIs and charts at retailer level. In the overall dashboard, the user can compare retailers with each other on full market level. Both dashboards therefore serve different purposes (i.e. retailer level analysis versus market level analysis). To keep the data structured, the data from the pivot tables is stored on two different tabs within the tool. The data for the retailer dashboard is stored in the *Retailer dashboard data*. The data for the overall dashboard is stored in the *Overall dashboard data* tab. Within the *Retailer dashboard data* tab, nine different pivot tables are created to calculate and display the data that will show up in the dashboard. For the *Overall dashboard data* tab, also nine different pivot tables are created with the same purpose as the *Retailer dashboard data* tab. The calculations in both dashboards mainly consists of percentages that show if a certain PDP element or is present or not on the corresponding PDP. In Figure 19, the schematic overview of the data analysis in the tool architecture is shown.

5.1.3.3. Graphical user interface

To get from data and information to knowledge, the graphical user interface plays a key role. The information in the data analysis generated by the different pivot tables is turned into a structured dashboard that shows the data according to the selected input filters of the users. In this way, the user only sees the data that it specifically wants to see in order to take actions (Mandinach et al., 2006). For further analysis, the tool allows the user to make more detailed analysis by presenting a list of the PDPs that do not have sufficient content quality in the form of drill-down tabs. This is done by clicking on a KPI in the retailer dashboard. The drill-down tabs within the tool are also part of the graphical

user interface and can be navigated to from the dashboard and vice versa. An overview of the drill-down tabs is given in Appendix I.

5.1.4. Data quality

Since it is crucial for the reliability of the tool that the data is reliable, several checks on the input data were done to improve the data quality of the dataset. For every relevant data quality dimension that were defined earlier through the expert analysis and literature, the implementation within the monitoring tool is shown in Table 10. For the scraped data, there are four main changes made to the data to improve the accuracy of the data. The changes made to the dataset regarding data quality are found in appendix D.

Table 10 – Implementation of relevant data quality dimensions

Data quality dimension	Implementation in monitoring tool
Believability	The data is regarded as true by the users since it is scraped directly from PDPs. Random checks also have been done to verify the validity of the data.
Accuracy	The data is regarded as accurate and error free except for four variables. For the variables that were not accurate, changes have been made (see Appendix D).
Value-added	The data adds value to the company since it makes it possible, with several calculations, to monitor the content quality on PDPs across different online retailers.
Relevancy	The data is relevant for the tool since it meets the users' need in the data that they want insights to. With the data it is possible to make decisions and take actions.
Timeliness	The data that is used in the tool can be updated by the user at every moment in time. The data that is used is at most one day old and for the purpose of this tool, this is sufficient.
Completeness	In the datasets delivered by the scraping software, no incomplete data has been detected (empty values or null values). For this reason, no automatic checks are done to fill in or repair the data.
Appropriate amount of data	The amount of data that is used is, is substantial. Scraped data for one day for every online retailer typically consists of 70000 values (excluding calculations). For Microsoft Excel, these amounts of data could quickly become a problem and make loading times longer. For this reason, every 4 months the data will be removed from the tool and stored elsewhere to ensure the usability of the tool for the user.
Interpretability	The data definitions that are used are appropriate and clear for the users.

Ease of understanding	The data itself is clear and comprehensible for most users. For unclear or ambiguous data, written explanations are given within the tool to inform the user.
Accessibility	The data is easily retrieved by downloading the raw data from the scraping software and copy this into the monitoring tool. For this process, also a manual is written for the users.

5.1.5. Tool interface design (RQ5)

For the development of the interface design of the tool, various scientific sources related to dashboard design were used. Since the tool has a “pull” scenario type of dashboard, the charts and other dashboard elements need to be visually appealing and offer support to explore and filter the data (Janes et al., 2013). For the development of the interface of the tool, the identified dashboard characteristics by Malik (2005) for dashboard design, dashboard layout and dashboard navigation are implemented to present the data in an effective and aesthetically appealing way to the user.

Basic- and enhanced dashboard characteristics

The basic- and enhanced characteristics stated by Malik (2005) for an enterprise dashboard are for the most part implemented in the tool. The enhanced *collaborative* characteristic is not implemented in the tool because since dashboard does not have a build in function to exchange results with other users. This option, however, is not found relevant for this tool since results are discussed within team meetings and in these meetings, screenshots are mostly used to show the results. An option to exchange the results from the tool is therefore seen as redundant by the users of the tool. Furthermore, there is no *trackability* option within the tool. Since the customization of the KPIs that are shown the dashboard to the likings of the user is a very advanced feature, this option was not considered a must have. In the tool however, it is possible for the user to filter the data on different elements (e.g. retailer, date, product category and product status). In Table 11 the implemented basic- and enhanced dashboard characteristics into the tool are presented.

Table 11 - Implemented basic- and enhanced dashboard characteristics

Dashboard characteristic	Implementation in tool
Synergetic	The dashboard is ergonomically and visually effective and therefore the user is able to synergize information on both dashboard screens
Monitor KPIs	The dashboard displays the critical KPIs for effective decision making
Accurate	The information that is used is accurate (see Appendix C for more information on the data quality improvements)
Responsive	The dashboard is responsive in the sense that certain KPI values have different color codes (e.g. score of 100% is green, 40% is red)

Timely	The tool displays the most recent imported scraped data. It is always possible to update the data at any given moment
Interactive	It is possible for the user to drill-down and get to the details in the drill-down tabs
More data history	It is possible for the user to view historical trends for KPIs (e.g. availability trend in the retailer dashboard)
Personalized	The dashboard presentation is user specific since the user can click on “their” own retailers to see relevant information
Analytical	It is easy for the user to navigate through the drill-down tabs, make analyses and compare data with the different filter options

Dashboard design elements

During the development of the tool design, different design elements by Malik (2005) were used. In Table 12, the implemented dashboard design elements are elaborated.

Table 12 - Implemented dashboard design elements

Dashboard design element	Implementation in tool
Screen graphics and colors	The colors used throughout the tool are not distracting and are also used as functional elements (i.e. colors used to show if a KPI has a good (green) or bad (red) score)
Appropriate chart types	The chart types are validated by the users for appropriateness. Two types of charts are used: column- and line charts
Animation with relevance	The tool uses one animation to interact with the user. When clicking on the different KPI scores, a pop-up screen appears with the explanation of the KPI score. Since the tool was restricted to be designed within Microsoft Excel, implementing more advanced animations was not feasible
Optimal content placement	To keep the dashboards clear and uncluttered, only the relevant content is shown. Also, the most important KPIs are placed on top and the less important KPIs and charts lower on the screen

Dashboard layout elements

For the layout of the monitoring tool, the four identified elements that are important for the layout of a dashboard (Malik, 2005) were used. In Table 13, the implemented dashboard layout elements are elaborated.

Table 13 - Overview of implemented dashboard layout elements

Dashboard layout element	Implementation in tool
Number of windows and frames within the dashboard	The number of frames and windows on the dashboard are limited to keep the text readable and prevent the user from being too overwhelmed
Symmetry and proportions	For the tool only straight shapes and lines are used. The size and proportions of the KPIs correspond to the importance of the KPI (i.e. basic content score and extended score are bigger than the separate elements)
Computer screen resolution	The tool can be used and is scalable for every screen resolution. To prevent that users with a lower screen resolution have to scroll horizontally, a modest number of windows are used in the dashboard
Context selection	For the placement of the different KPIs and charts, input from the end-users was used to determine if the all content was placed in the right windows and frames

Dashboard navigation elements

Lastly, regarding the navigation within the monitoring tool, the three identified elements regarding dashboard navigation (Malik, 2005) were implemented into the tool. In Table 14, the implemented dashboard layout elements are presented.

Table 14 - Overview of implemented dashboard navigation elements

Dashboard navigation element	Implementation in tool
Information grouping and hierarchy	Information is grouped ordered within the dashboard. For the retailer dashboard there are 6 categories (content quality, reviews, portfolio coverage, buybox retailer, pricing and availability). In the overall dashboard there are 4 categories (portfolio coverage, content quality, availability and pricing)
Tabs and pivots	The dashboards contain two dashboard tabs and 17 different tabs to drill-down on information. In every drill-down tab, a link to get back to the retailer dashboard is present at the top of the screen. Pivot tables are used to do the drill-down analysis
Context drill-down	The user is able to drill-down in to see additional details when a specific KPI or chart is clicked on

5.1.6. Tool design & layout

To show the KPIs and charts two dashboard tabs have been designed: a retailer dashboard and an overall dashboard. The retailer dashboard shows the user the KPIs and charts at retailer level. If the user wants to compare KPIs between different retailers, he or she will use the overall dashboard where

all retailers are compared. For the design for both dashboards, theory on dashboard design has been used throughout the development process. Since the dashboard has a pull scenario (i.e. the user wants specific information and uses the dashboard to obtain it), the charts are visually appealing and it offers support to explore and filter the data (Janes et al., 2013).

Retailer dashboard tab

The retailer dashboard contains six different KPI elements (as mentioned in the GQM model), the design of the upper half of the dashboard is shown in Figure 22. The company names of the retailers are anonymized and are available upon request with the author.

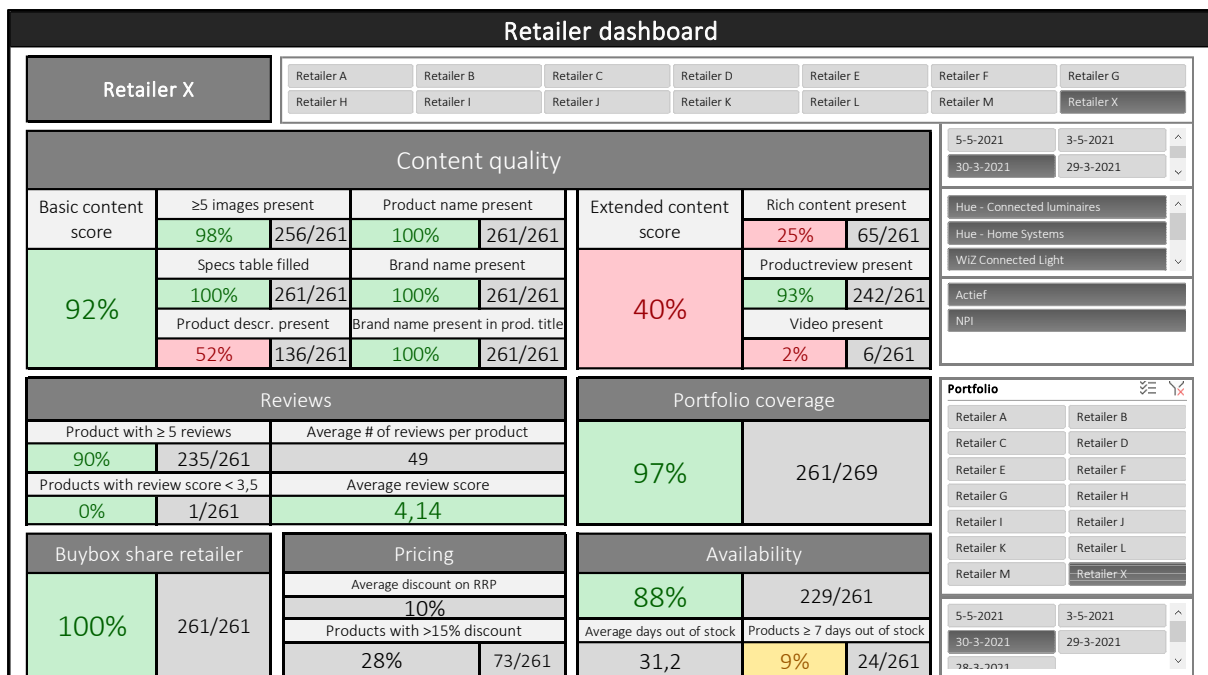


Figure 23 - Initial design retailer dashboard

The main component of the dashboard is the content quality. For this KPI, the overall basic content score and the extended scores are shown together with every aspect of both scores shown separately. The separate scores per PDP element are also shown besides the overall content scores to see where possible improvements can be made. Furthermore, the KPIs of reviews, portfolio coverage, the buybox share of the retailer, product pricing and availability for every retailer is shown on the retailer dashboard. To be able for the user to make a distinction between different retailers (the user is responsible for their own set of retailers), the user can filter on the retailer that they want to have insights in. This is done by clicking on the retailer at the top of the screen. The KPIs are color coded to represent the importance of improving the content quality. The value ranges for every color as shown in Table 6 are used as threshold values. Furthermore, filtering on different dates, product categories and product status can also be done within the dashboard by just clicking on the buttons on the right

side of the screen. On lower half of the retailer dashboard tab, three different charts are used to give insights in the buybox distribution, product availability per product category and product status and the pricing that the retailers use compared to the RRP. An overview of the complete retailer dashboard design can be found in Appendix G. To inform the user about the meaning of all different KPIs, an explanation within the tool is given when hovering the mouse over a certain a KPI. An example for the buybox share is given below in Figure 23. Explaining what all elements mean to the user helps with the interpretability and ease of understanding of the data shown in the tool (Wang & Strong, 1996).

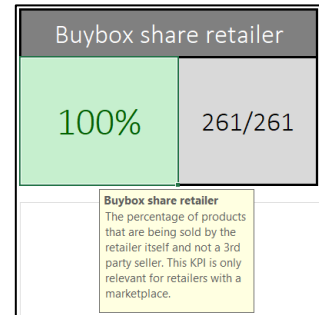


Figure 24 - Example of information pop-up for the buybox share

Overall dashboard tab

The overall tab consists of nine charts that are divided over four different subjects: portfolio coverage, content quality, product availability and pricing. Figure 24 shows the content quality part of the overall dashboard, in Appendix H the complete overall dashboard is shown for the initial design.

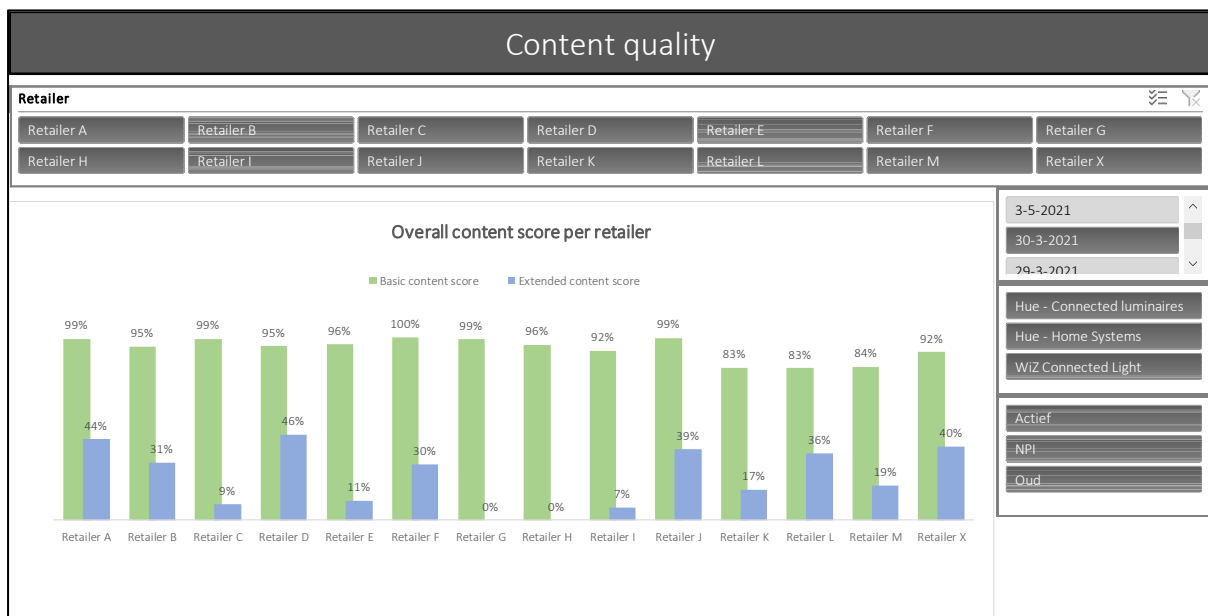


Figure 25 - Content quality in overall dashboard

The purpose of the overall dashboard is to give an overall overview of the different subjects that can be scraped from the PDPs for all retailers. With the charts in the overall dashboard, retailers are compared with each other and differences between them are quickly noticeable. Also, in the overall dashboard, it is possible to filter on the different retailers (if this is needed), the date, the product category, and the product status.

Drill-down tabs

To improve PDPs with insufficient content quality, the user needs to know for which products the content quality is insufficient. Both dashboards give a quick overview on the different KPIs, but it is not directly possible to see which products miss certain elements. For this reason, the tool let the user navigate through different drill-down paths. Via the dashboard it is possible to click on the specific element that the user wants to investigate further and get more details about it. In total there are 17 drill-down tabs, a list of these tabs is presented in Appendix I. An example of a drill-down tab, in this case the availability of the products from Retailer X, is shown in Figure 25. This particular tab shows the products that are seven days or more out of stock. The user is also able to filter on the date, the retailer, the days that the product is out of stock, the product category and the product status.

Status/EAN	Product name	# days out of stock
NPI		
8718699784775	Hue Lightstrip Pixelated TV 65' EU	47
8718699784799	Hue Lightstrip Pixelated TV 75' EU	30
8719514266902	Philips HueW 5.5W Luster E14 EU 2p	15
8719514279131	Hue Filament G125	11
Actief		
8718696695265	Philips HueAmbiance GW B39 E14 EU 2P	137
8718696168875	Philips Hue Explore vloerlamp - warm tot koelwit licht	137
8718696162712	Philips Hue Cher plafondlamp - warm tot koelwit licht - zwart - met voet	130
8718699704803	Philips Hue HDMI Sync Box EMEA	101
8718696168615	Philips Hue Being hanglamp - warm tot koelwit licht - zwart	90
8718696175699	Philips Hue Buckram opbouwspot - warm tot koelwit licht - 4-lichts - zwart	36
8718696695203	Philips HueAmbiance GW B39 E14 EU	36
8718696174524	Signe Hue floor lamp aluminium 1x32W 24V	35
8718696175873	Philips Hue Aurelle plafondlamp - warm tot koelwit licht - rond	23
8718696174388	Resonate Hue WACA wall lantern black 2x8	22
8718696170557	Calla Large Hue ext. pedestal black 1x8	16
8718696170540	Welcome Hue White EU	16
8718696170526	Impress Hue WACA EU pedestal black 2x8W	14
8718696743157	Philips Hue DIM Switch EU	14
8718696175255	Devote Hue pendant white 1x9W 230V	13
8718696171554	Fugato plate/spiral white 4x5.7W 240V	11
8718699688820	Philips HueW xW FI AGO E27 EUR	10
8718696174371	Appear Hue WACA EU wall lantern black 2x	9
8718696170649	Fuzo Hue White EU pedestal black 1x15W	7
8718696170502	Impress Hue WACA EU pedestal black 2x8W	7
Eindtotaal		967

Figure 26 - Example of the drill-down tab for the availability

Use of the tool

The tool can be used by all sales and marketing employees at the Consumer Benelux department of Signify. A manual is written for every user where the purpose and working of the tool is explained. Furthermore, a step-by-step guide to import scraped data into the tool is also added to manual to allow every user to do this by themselves.

5.2. Results and analysis of testing the tool

In this section the outcomes of the initial tool testing and evaluation are reported and discussed. It concerns the evaluation through five sales and marketing experts using the tool for a couple of days on three different criteria: usability, utility, and output. In addition to that, it is also determined if all design requirements for the tool are met. The implications and recommendations from the testing are used to identify improvements for the development of the final solution design.

Usability

To assess the usability the System Usability Scale (SUS) was used (Bangor et al., 2008). The results from the SUS method for usability testing are shown in the table below. The assessment consists of 10 questions with a 5-point Likert scale where the answers range from “strongly disagree” to “strongly agree”. The final score per user ranges from 0-100, where higher scores indicate better usability. In Appendix J an overview of the survey questions and calculation method is shown.

Table 15 - SUS scores per participant

Role	SUS score
Key Account Manager #1	87.5
Key Account Manager #2	90
Key Account Manager #3	82.5
Key Account Manager #4	82.5
Channel Marketeer	85

The results from the SUS method, shown in Table 15, are very positive since every score is far above the minimum viability score of 68 and the mean SUS score of 85.5 is close to 90 which can be interpreted as a truly superior score for the usability. Only one questions was answered “neutral” (KAM #3), whereas all other questions were positively answered by all participants. This indicates that the monitoring tool is scoring high on usability.

Utility

For assessing the utility of the monitoring tool, a semi-structured interview was set up where the participants of the study could openly express their opinion on the utility of the tool. The three questions asked during the interview regarding the utility of the tool are as follows:

1. *Does the tool what it promises to do? Why or why not?*
2. *Is the intended output of the tool (improving the content quality on PDPs) a direct result of (using) the tool? Why or why not?*

3. *Are there missing functionalities within the tool? If yes, which functionalities?*

The outcomes of the semi-structured interview are analyzed and evaluated. With these outcomes, several improvements for the monitoring tool are composed.

For the first question on the promise of the tool the answers were quite the same for every participant. The ability to quickly see the important KPIs in a clear overview is mentioned multiple times as the fact that the tool does what it promises to do, for example one interviewee said that “I can quickly see the status of all products that are live and not live (i.e. portfolio coverage) for my accounts, this is something I could not do before” and another statement was made that “with one press on the button I can directly see a complete overview of the status of the essential eCommerce elements. From different content quality levels to the availability of products. It is all there.” Furthermore, the ability to customize and filter for different elements is something that made the tool very functional “it is very easy to filter on different levels (e.g. product groups, product status and dates) to get the info you want to see”.

The intended output of the tool is to make it possible to mass monitor the PDP elements across different online retailers and take actions based on this in order to improve the content quality. This is seen as a direct result of the tool by all interviewees. One interviewee (KAM #2) mentioned that “it is impossible to track, maintain and improve the elements of the PDP for every product at every retailer manually, this would be way too time consuming. Through the tool I can quickly see which PDPs need attention and which actions or projects need to be initiated within my KAM team to improve the identified PDPs”. Also, the ability to monitor if retailers adhere to the contractual agreements regarding the content quality on their PDPs is also mentioned (KAM #3) as a direct output of the tool “I can see exactly how retailers score on the different PDP elements stated in the contracts with retailers. Without this tool this would be impossible to do and we, as being Signify, have no leg to stand on regarding this subject”.

The interviewees also mentioned some things that, in their opinion could be adjusted or added to better serve their needs (i.e. missing functionalities). The possibility to filter on a custom group of products was one of the things that could be added so that the user of the tool could monitor their own list of products on all different aspects. An interviewee (KAM #2) said that “it would be helpful to have the possibility to filter on a custom list of products that you can edit at any time, for example to monitor new product introductions or current promo products”. Also, a minor improvement for the calculation of the basic content score is mentioned (KAM #3) “for the calculation of the basic content score I would exactly copy the requirements from the contractual agreements with retailers, so it is easy for me to see the basic content score of the retailer and based on that determine the

consequences for the retailer”. Furthermore, it was also mentioned that the way that the extended content score is calculated should be adjusted since not every retailer had the possibility to have rich content present on the PDPs itself but do this via other ways, like a brand page. One of the experts (channel marketer) said that “I would change the way that the extended content score is calculated and would not include rich content in this calculation since, for example bol.com, does not give us the possibility to have rich content present on their PDPs but they do offer rich content in the form of a brand page”. The current calculation would give a wrong impression on how well the retailer would score on the extended content quality since for rich content the score would always be “0%”. The last improvement that is mentioned (KAM #2) is that it would be helpful to see the evolution of the availability for selected products over time instead of just the real time availability. He said that “I am also interested in the evolution of the availability for selected products over time, this would be more valuable than the availability at a certain moment. With this information possible actions regarding availability problems could be better identified”.

Output

The last part of the testing consisted of proving that the content quality on the PDPs was improved by using the tool for identifying insufficient PDPs. With the help of the tool, several PDP elements were identified as ‘insufficient’ by the user and corresponding actions were taken to improve the content quality. In Table 16 below the changes from the situation before and after using the tool are shown. The complete list of products that were changed can be found in Appendix K.

Table 16 - Overview of changes in KPI score

Retailer name	Product range	KPI name	Initial score		Action taken	Improved score	
Retailer X	Philips Hue	Product descr. Present	44%	99/224	Uploaded product description to retailer	72%	162/224
Retailer E	WiZ Connected	≥5 images present	5%	1/21	Uploaded missing mages to retailer	95%	20/21
Retailer A	Philips Hue & WiZ Connected	Specs table filled	96%	256/270	Uploaded specifications to retailer via supplier portal	100%	275/275
Retailer A	Philips Hue	Video present	39%	104/270	Uploaded videos to retailer via supplier portal	100%	275/275

The results from testing the output are very promising. The goal of testing the direct output was to see if the monitoring tool was able to identify PDPs with insufficient content quality and to see a difference in the content score when the improvement actions were made. One participant (KAM #3)

mentioned that after he uploaded videos via the supplier portal of Retailer X to the PDPs that were missing the product video that “It gives extra motivation to see the positive change in the content score when I uploaded the videos for the PDPs. It gives me the feeling that I’m in control of what I am doing and can actually see that it is working!”.

Tool requirements

To show how the design requirements for the monitoring tool are met, for every requirement it is stated in Table 17 how this is done.

Table 17 - Implementation of tool requirements

Requirement	Implementation in tool
1. <i>The tool should support Signify in monitoring and managing the online content quality at different retailers (company requirement).</i>	The tool supports the users in monitoring and managing the content quality presenting different KPIs and charts for different retailers.
2. <i>The tool will have a dashboard with different KPIs and charts that are important to monitor and manage the online content quality (literature and company requirement).</i>	The tool has a dashboard that show the relevant KPIs and charts for managing the online content quality.
3. <i>The tool should provide content quality information on both retailer and product level (company requirement).</i>	It is possible to show content quality on retailer and product level by using the filtering options in the tool.
4. <i>The tool should provide a content score to assess the content quality based on business rules (company requirement).</i>	The content score is calculated based on internal business rules at Signify and this score is shown in the retailer dashboard. The separate elements that determine the content score are also visible in the dashboard.
5. <i>The tool should be able to let the user of the tool make their own analysis and allow the user to drill-down within the tool (literature and company requirement).</i>	The user can make his / her own analysis based on the KPIs shown in the dashboard. The user can click on a certain KPI to make more advanced analyses and drill-down for more detailed information.
6. <i>The tool should be user friendly. This means that it must be easy to navigate between different tabs and simple to obtain the results the user wants to see (literature and company requirement).</i>	The user can easily navigate through the tool with direct links to different tabs within the tool. The ease of use of the tool is also endorsed by the high SUS score regarding the usability.
7. <i>The KPIs and charts within the tool should be easy to understand. This means that KPIs and charts should be self-evident or</i>	The KPIs and charts are easy to understand without the need of expert knowledge. If a KPI is still unclear for the user, an explanation

<i>an explanation should be present (literature and company requirement).</i>	pops up when clicking on the KPI (see Figure 22).
8. <i>The tool should be able to show results that are specifically relevant for different users (literature and company requirement).</i>	Within the tool, the user can choose only the retailer(s) that it wants to see the results for. Furthermore, it is possible for to filter on the data, product category and product status so that the user gets the relevant results.
9. <i>The purpose of tool should be clear for the user (literature and company requirement).</i>	The purpose of the tool, giving insights monitoring and improving online content quality, is clear for the users. From the answers regarding the utility test, it is evident that the users know what the intention of the tool is and what it is able to do.
10. <i>The tool should comply with present legal requirements (company requirement).</i>	The most important legal requirement the tool needed to comply with, was the fact that is not allowed to track prices from retailers and use this knowledge during contractual negotiations with other retailers to gain a better negotiation position. For the users of the tool, this rule was already clear and therefore price tracking will only be used for internal analyses and not during price negotiations with retailers.
11. <i>The tool is for internal use at Signify (company requirement).</i>	The tool will only be used within the sales and marketing department for the consumer Benelux region. It is not allowed to use the tool externally.
12. <i>All data that the tool uses should be accurate, timely and complete (literature and company requirement).</i>	The tool data is tested by considering the data quality dimensions (Wang & Strong, 1996) and is improved on data accuracy (Appendix D) Furthermore, the data is timely since it can be updated whenever the user wants with the most recent data. Lastly, no incomplete data has been detected and therefore the data is regarded as complete.
13. <i>The tool must be designed within Microsoft Excel (company requirement).</i>	The tool is designed in Microsoft Excel.

Improvements

Based on the results from the three different tested criteria of the monitoring tool, several improvements and changes are identified and stated below.

- Addition of the ability to filter on a custom list of products that the user of the tool can edit at any time.
- The calculation for the basic content score needs be adjusted to exactly match the contractual agreements with retailers so that the user of the tool can directly see how the retailer is scoring for different PDP KPIs.
- The calculation for the extended content score needs to be adjusted because the majority of the retailers are not able to show rich content on the PDPs itself but do have a brand page which includes rich content. For this reason, rich content on the PDP is something that still should be measured but not considered for the extended content score but as a standalone KPI that is relevant for a small number of retailers.
- Changing the chart that allowed to see how many products were out of stock for 7 days or more per product category on a selected date, to a chart that allowed for seeing the evolution of the availability over time.

5.3. Final solution design

In this section, the final solution design is discussed. The initial tool design was improved based on the outcomes of the testing and evaluation. The four identified improvements have been integrated in the new and final design. Figure 26 shows the upper half of the final design of the retailer dashboard. In Appendix L, the final solution design of the retailer dashboard is presented. Other parts of the monitoring tool have not been adjusted and are therefore left out in Appendix L.

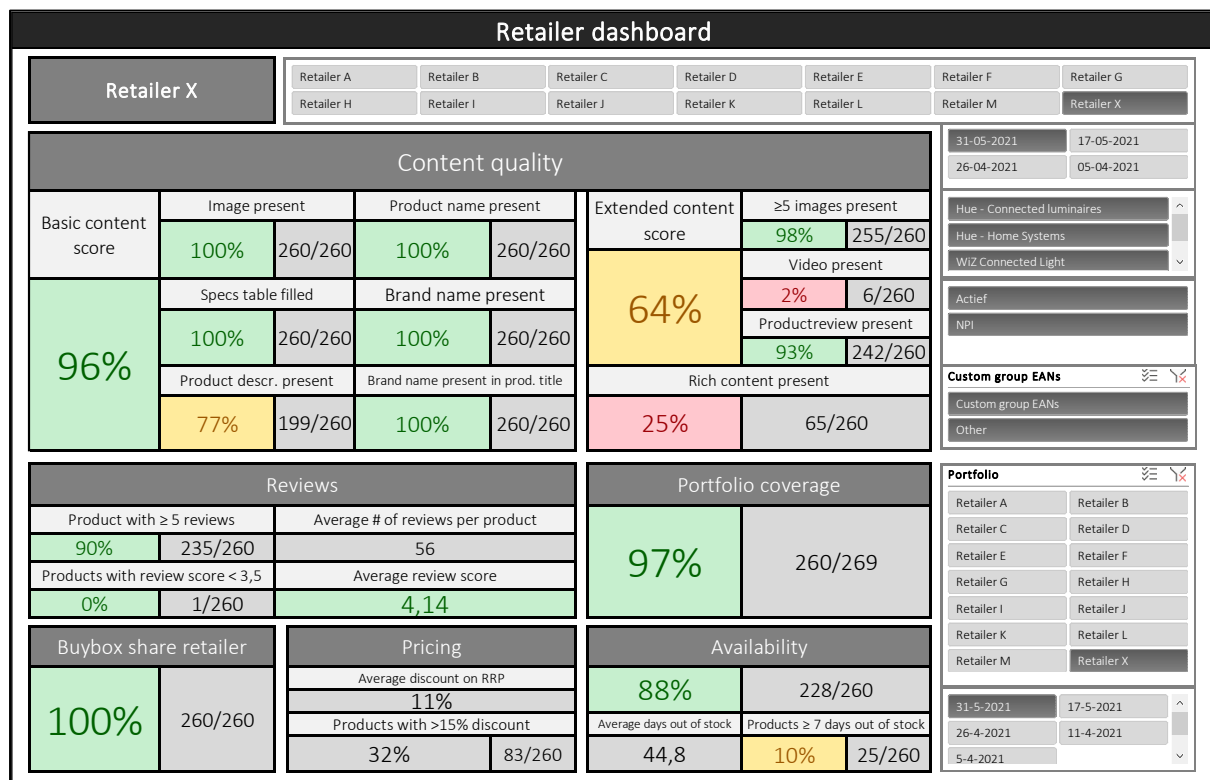


Figure 27 - Final solution design retailer dashboard

The first adjustment that was made to the retailer dashboard is the addition of the feature to filter on custom products via a list where the user can put the EAN number of the products he or she wants to see. On the right side in the retailer dashboard it is now possible to filter with one click on “custom group EANs”. Via the tab “Custom group EANs”, the user can fill in the list of products. Furthermore, adjustments are made regarding the calculation method for both the basic content score and the extended content score following the input from the users during testing. For the basic content score, the first element of the formula was changed from “% ≥ 5 images present” to “% image present” to exactly match the contractual agreement with retailers. The adjustment made to the extended content score was the omission of “% Rich content present” and the addition of “% ≥ 5 images present”. This was done to prevent retailers from scoring low on the extended content score, when in fact they

could have acquired rich content in different ways than that the standard rich content format that the scraping software measures (e.g. a brand page). The new formulas that are used are stated below:

$$\text{Basic content score} = \frac{\% \text{ image present} + \% \text{ specs table filled} + \% \text{ product description present} + \% \text{ product name present} + \% \text{ brand name present} + \% \text{ brand name present in product title}}{6}$$

$$\text{Extended content score} = \frac{\% \geq 5 \text{ images present} + \% \text{ video present} + \% \text{ productreview present}}{3}$$

Lastly, the second chart in the initial retailer dashboard (Products ≥ 7 days out of stock per product category) has been replaced by a chart that shows the development of the out-of-stock situation over time. Via a slicer, the user can select the range of dates where he or she wants to see the availability for. In Figure 27 the added chart is shown.

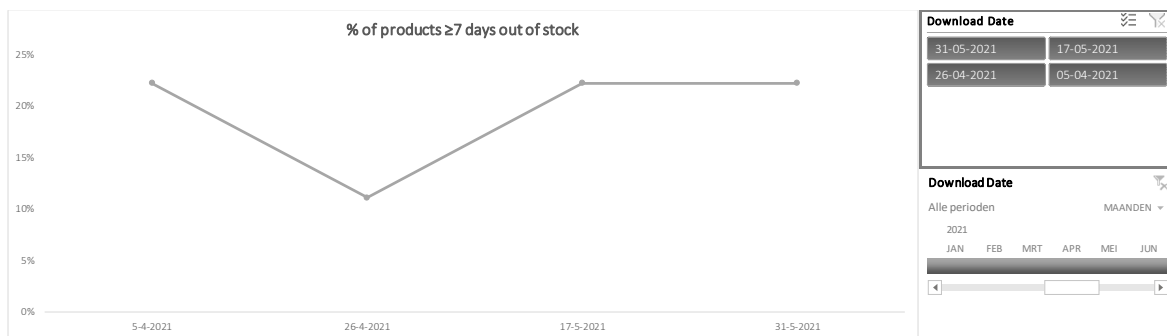


Figure 28 - Out of stock chart in retailer dashboard

6. Conclusion & Discussion

In this chapter the conclusion and the discussion are described. In the conclusion, an answer is given to the main research question. In the discussion part, theoretical and practical implications of the research are presented. Lastly, the limitations of this study and suggestions for future research are described.

6.1. Conclusion

The goal of this research was to improve the manageability of online PDP elements by developing a tool that is able to monitor and assess the content quality. The result is a monitoring tool, constructed in Microsoft Excel, that can be used for monitoring the content quality at online retailers and ERT-channel retailers within Signify. This process and development of the tool gives answer to the main research question:

How can a software tool be designed to facilitate mass monitoring of online product detail page elements to manage the product page content quality and therefore improve the conversion rate?

Mass monitoring of the online PDPs is facilitated by using scraped PDP data and transform this into useful insights with the help of two dashboards and several drill-down tabs. By using theory combined with empirical research design requirements were identified in order to develop the tool. With the tool, employees at Signify are now able to track how well different retailers are scoring on the content quality and can directly take actions to improve the content based upon different lists of products that have insufficient content quality. This was not possible before and compared to manually checking PDPs, this tool is saving a lot of time. The tool gives insights into six different PDP elements: content quality, reviews, portfolio coverage, buybox share, pricing and availability. The two dashboards make it possible to get insights on both retailer- and overall level. The user of the tool is able to filter on five different dimensions to get the data that he or she wants to see. The dimensions consist of retailer, data, product category, product status and custom group EANs. These features help to reach the main goal of the tool of managing and assessing the content quality across different retailers in an easy and sustainable way in order to reach the end goal of improving the conversion rate. Via the drill-down tabs, lists of PDP elements with insufficient content quality are shown. In these drill-down tabs, the user is able to make more detailed analyses and improve the identified insufficient PDPs. Besides the ability to manage and assess the content quality score, also the ability to compare and benchmark scores and results between different retailers in the overall dashboard is something that will stimulate the focus on improving the content quality within Signify. Lastly, the possibility to check on additional PDP elements (e.g. product prices and product availability) is useful for managers and could be used as input for strategic purposes (e.g. prices changes or supply chain related issues).

6.2. Practical implications

With the monitoring tool, Signify has a tangible asset that is ready to be implemented and used by the sales and marketing employees. This research offers several practical implications since the tool is specifically developed and tested for internal use at Signify.

First, the tool delivers insights into the online content quality of products and other elements that are present on the PDPs of different retailers. With generating these insights alone, nothing will change regarding the online content quality. For this reason, the monitoring tool should be used as a supportive software program to reach another goal. The tool shows results and lists of products that have insufficient content quality, but it is crucial that for the user follow-up actions need to be taken by the user itself in order to improve the online content quality. To ensure that the tool will be used and has an impact, a detailed plan to implement the tool should be constructed. Some users will be hesitant to use the tool since they rather want to do things their own way or see the tool as extra workload. For this reason, it is important to inform and train the users in using the tool and see the added value of the tool. Because the tool data is quite static (not a lot of changes regarding the content of products change every day), the tool should be ran once a week at the beginning. This could be changed to once a month later when the content quality has been improved across all retailers and is under control. Another implication of the tool is that it is possible to track and benchmark the results and KPIs between retailers. From a managerial point of view this could be interesting to discuss these results occasionally with the sales and marketing team and see where improvements are possible. Lastly, the tool should have an owner within Signify. This ensures that the quality of the tool is guaranteed and that possible questions regarding the use of the tool can be answered by this owner. Also, for updating product lists or expanding the different types of elements that are scraped, a tool owner would be necessary to manage and develop this.

6.3. Theoretical implications

For this research, the amount of available literature about monitoring content quality was scarce. However, different theoretical aspects relevant for developing the tool have been analyzed and combined in to reach the goal of this research. This study offers a theoretical contribution to the literature of online content management in general and specifically in relation to online product detail pages. The first thing that adds to the literature, is that this research is combining research on online conversion rate, data-driven DSS, data quality and dashboard design. For the determination of factors that serve as input for assessing the content quality, theory on online conversion rate was used together with company expert input. For the development of the tool several models and frameworks have been used to substantiate different decisions made within the process. Since a tool for

monitoring online content on PDPs was not researched and developed yet in current literature, the research gap that is filled with this study, is that it uses literature on different software development domains (data-driven DSS, data quality and dashboard design) in order to design a tool for monitoring and assessing online content quality. The combination of these different research domains into the development of a tool makes this study unique and is therefore adding value to current literature. Lastly, the multi-methodological approach of this research that consists of the theoretical analysis, collection of qualitative data (i.e. expert interviews) and testing for validation, resulted in an integrated tool based on different viewpoints. For this reason, it also adds to literature as a comprehensive overview on the PDP elements that are relevant for, in this case, selling to online retailers.

6.4. Limitations and future research directions

This research was subject to some limitations that are elaborated in this section. Furthermore, for further exploration, several future research directions are presented.

The first limitation is regarding the immature research domain where this study is focusing on. There is little scientific literature available about measuring and using PDP elements in order to assess the online content quality. For this reason, the theoretical basis on which the elements that affect the conversion rate are determined is not very substantial. Future research on this topic could help with filling this research gap and could empower the assumptions that have been made in this research. Secondly, for the testing the output of the tool, only one test has been done due to time constraints of the researchers' thesis period. For this reason, the tool could not be validated over a longer period of time and it was not possible to do a second iteration of testing (beta test). To overcome this limitation, future research should include extra testing of the tool to enhance the validity and generalizability of the tool. Thirdly, the development program of the tool was limited to be in Microsoft Excel due to practical reasons. This however prevented the researcher in using some features that were described in literature to be useful in the development of data-driven DSS and dashboards (e.g. alerts and triggers). Furthermore, Microsoft Excel is not the best program to handle big data and this could make the tool run more slowly when lots of data have been imported. To overcome this problem, the option to construct the tool in different software programs should be given to allow the developer better suited equipment for designing the tool. Lastly, the frame of reference of the participants during the interviews and tests is limited to the boundaries of their knowledge on the subject of online content quality. It could be possible that certain valuable knowledge about online content quality did not come forward during the interviews and therefore has not been included during the development of the tool. Furthermore, it could be that daily routine task thinking is used by the participants during the interviews. To avoid this problem in future

research, the researcher must consider to instruct the participants to think beyond their frame of reference and to think outside the box.

Besides the already mentioned future research directions, two other research directions could be interesting to further explore. Firstly, it could be interesting to test if using the tool and improving the online content quality is directly correlated with improving the conversion rate at retailers. Since these assumptions are based on few and immature research, there are research possibilities to confirm or deny the relation between the content quality of PDPs and the conversion rate. Secondly, the use of the tool could be expanded to use in other product types and domains. For Signify, it could be interesting to implement this tool, with some adjustments, for other product groups (e.g. traditional lighting) and to other markets (e.g. global regions).

7. References

- Ackoff, R. (1989). From Data to Wisdom. *Journal of Applied Systems Analysis*, 16, 3–9.
<https://doi.org/10.5840/du2005155/629>
- Ayanso, A., & Yoogalingam, R. (2009). Profiling retail web site functionalities and conversion rates: A cluster analysis. *International Journal of Electronic Commerce*, 14(1), 79–114.
<https://doi.org/10.2753/JEC1086-4415140103>
- Baker, L. (2018). *Amazon's Search Engine Ranking Algorithm: What Marketers Need to Know*.
<https://www.searchenginejournal.com/amazon-searchengine-ranking-algorithm-explained/265173/>
- Bangor, A., Kortum, P. T., & Miller, J. T. (2008). An empirical evaluation of the system usability scale. *International Journal of Human-Computer Interaction*, 24(6), 574–594.
<https://doi.org/10.1080/10447310802205776>
- Basili, V. R., & Caldiera, G. (2000). The Goal Question Metric Paradigm. *Encyclopedia of Software Engineering - 2 Volume Set*, 2, 528–532.
<https://www.cs.umd.edu/~basili/publications/technical/T89.pdf>
- Basili, V. R., Caldiera, G., & Rombach, D. (1994). Goal Question Metric Paradigm. In *Encyclopedia of Software Engineering* (1st ed.). Wiley & Sons.
- Basili, V. R., Lindvall, M., Regardie, M., Seaman, C., Heidrich, J., Münch, J., Rombach, D., & Trendowicz, A. (2010). Linking Software Strategy through and Business Development Measurement. *IEEE Computer Society*, April, 57–65.
- Batini, C., & Scannapieco, M. (2006). *Data Quality: Concepts, Methodologies and Techniques*. Springer. https://doi.org/10.1007/978-1-4020-4749-5_4
- Blumberg, B., Cooper, D., & Schindler, P. (2011). *Business research methods* (3rd ed.). McGraw-Hill Higher Education. <https://www.worldcat.org/title/business-research-methods/oclc/706776183>
- Brath, R., & Peters, M. (2004). Dashboard design: Why design is important. *DM Direct*, 85.
[https://doi.org/10.1016/s1359-6128\(97\)82935-7](https://doi.org/10.1016/s1359-6128(97)82935-7)
- Brooke, J. (1996). Sus: a “quick and dirty” usability. *Usability Evaluation in Industry*, 189.
- Cáñez, L., Platts, K., & Probert, D. (2000). Industrial Make or Buy Decisions: Developing a framework for make-or-buy decisions. *International Journal of Operations & Production Management*.

- Codd, E. F., Codd, S. B., & Salley, C. T. (1993). Providing OLAP (on-line Analytical Processing) to User-analysts: An IT Mandate. *Codd and Date*, 32, 3–5. <https://ci.nii.ac.jp/naid/10020853884>
- Denyer, D., Tranfield, D., & Van Aken, J. E. (2008). Developing design propositions through research synthesis. *Organization Studies*, 29(3), 393–413. <https://doi.org/10.1177/0170840607088020>
- Di Fatta, D., Patton, D., & Viglia, G. (2018). The determinants of conversion rates in SME e-commerce websites. *Journal of Retailing and Consumer Services*, 41(October 2017), 161–168. <https://doi.org/10.1016/j.jretconser.2017.12.008>
- Dresch, A., Pacheco Lacerda, D., & Antonio Valle Antunes Jr., J. (2014). Design science research. In *Computing Handbook, Third Edition: Information Systems and Information Technology*. <https://doi.org/10.1201/b16768>
- Eckert, C., Stacey, M. K., & Clarkson, P. J. (2003). The spiral of applied research: A methodological view on integrated design research. *Proceedings of the 14th International Conference on Engineering Design*, 03.
- English, L. P. (2009). *Information quality applied: Best practices for improving business information, processes and systems*. Wiley Publishing.
- Eppler, M. J. (2006). *Managing information quality: Increasing the value of information in knowledge-intensive products and processes*. Springer Science & Business Media.
- Few, S., & Edge, P. (2007). Dashboard Confusion Revisited. *Perceptual Edge*, 1–6.
- Floyd, K., Freling, R., Alhoqail, S., Cho, H. Y., & Freling, T. (2014). How online product reviews affect retail sales: A meta-analysis. *Journal of Retailing*, 90(2), 217–232. <https://doi.org/10.1016/j.jretai.2014.04.004>
- Gudigantala, N., Bicen, P., & Eom, M. (Tae in). (2016). An examination of antecedents of conversion rates of e-commerce retailers. *Management Research Review*, 39(1), 82–114. <https://doi.org/10.1108/MRR-05-2014-0112>
- HIQA. (2011). *International Review of Data Quality Health Information and Quality Authority (HIQA)*. <http://www.hiqa.ie/press-release/2011-04-28-international-review-data-quality>
- Janes, A., Sillitti, A., & Succi, G. (2013). Effective dashboard design. *Cutter IT Journal*, 26(1), 17–24.
- Janes, A., & Succi, G. (2009). To pull or not to pull. *Proceedings of the Conference on Object-Oriented Programming Systems, Languages, and Applications, OOPSLA*, 889–894. <https://doi.org/10.1145/1639950.1640052>

- Light, D., Wexler, D., & Heinze, J. (2004). How Practitioners Interpret and Link Data to Instruction: Research Findings on New York City Schools' Implementation of the Grow Network Daniel. *The Annual Meeting of the American Educational Research Association*, 5, 22.
http://www.cct.edc.org/sites/cct.edc.org/files/publications/Grow_AERA04_fin.pdf
http://www.cct.edc.org/admin/publications/speeches/Grow_AERA04_fin.pdf
- Liu, P. C., & Zinn, W. (2001). Consumer Response to Retail Stockouts. *Journal of Business Logistics*, 22(1), 49–71.
- Loshin, D. (2001). *Enterprise knowledge management: The data quality approach*. Morgan Kaufmann.
- Loshin, D. (2006). Monitoring data quality performance using data quality metrics. *Informatica Corporation*.
- Lyon, M. (2008). Assessing Data Quality, Monetary and Financial Statistics. *Bank of England*.
- Maier, E., & Dost, F. (2018). The positive effect of contextual image backgrounds on fluency and liking. *Journal of Retailing and Consumer Services*, 40(July 2017), 109–116.
<https://doi.org/10.1016/j.jretconser.2017.09.003>
- Maio, N., & Re, B. (2020). How Amazon's E-Commerce Works? *International Journal of Technology for Business (IJTB)*, 2(1), 14–22. <https://doi.org/10.5281/zenodo.3894408>
- Malik, S. (2005). Enterprise Dashboards. In *John Wiley and Sons Inc* (Vol. 1).
- Mandinach, E. B., Honey, M., & Light, D. (2006). A Theoretical Framework for Data-Driven Decision Making. *Annual Meeting of AERA*, 1–18.
<https://pdfs.semanticscholar.org/70be/11b76e48eab123ef8a0d721accedb335ed5c.pdf>
- March, S. T., & Smith, G. F. (1995). Design and natural science research on information technology. *Decision Support Systems*, 15(4), 251–566.
- Maslen, R., & Lewis, M. A. (1994). Procedural Action Research. In *Proceedings of the British Academy of Management Conference* (p. 16).
- Morgan, A. J., & Inks, S. A. (2001). Technology and the sales force: Increasing Acceptance of Sales Force Automation. *Industrial Marketing Management*, 30(5), 463–472.
https://doi.org/10.1300/J375v14n01_07
- Moultrie, J., Clarkson, P. J., & Probert, D. (2007). Development of a design audit tool for SMEs. *Journal of Product Innovation Management*, 24(4), 335–368. <https://doi.org/10.1111/j.1540->

5885.2007.00255.x

- Muyllé, S., Moenaert, R., & Despontin, M. (2004). The conceptualization and empirical validation of web site user satisfaction. *Information and Management*, 41(5), 543–560.
[https://doi.org/10.1016/S0378-7206\(03\)00089-2](https://doi.org/10.1016/S0378-7206(03)00089-2)
- Nagaraj, A. (2019). *Amazon Product Listing 2020 Guide: Best Optimization & Guidelines*.
<https://www.sellerapp.com/blog/amazon-product-listing-guide/>
- Platts, K. W. (1993). A Process Approach to Researching Manufacturing Strategy. *International Journal of Operations & Production Management*, 13(8), 4–17.
- Power, D. J. (2002). *Decision Support Systems: Concepts and Resources for Managers*. Quorum Books.
- Redman, T. C. (1997). *Data quality for the information age*. Artech House, Inc.
- Santana, S., Thomas, M., & Morwitz, V. G. (2020). The Role of Numbers in the Customer Journey. *Journal of Retailing*, 96(1), 138–154. <https://doi.org/10.1016/j.jretai.2019.09.005>
- Scannapieco, M., & Catarci, T. (2002). Data Quality under the Computer Science perspective. *Computer Engineering*, 2(2), 1–12.
https://www.researchgate.net/profile/Tiziana_Catarci2/publication/228597426_Data_quality_under_a_computer_science_perspective/links/0fcfd51169a156b61a000000.pdf
- Sekaran, U., & Bougie, R. (2016). *Research Methods for Business* (Seventh). Wiley.
https://doi.org/10.1007/978-94-007-0753-5_102084
- Sim, J., Saunders, B., Waterfield, J., & Kingstone, T. (2018). Can sample size in qualitative research be determined a priori? *International Journal of Social Research Methodology*, 21(5), 619–634.
<https://doi.org/10.1080/13645579.2018.1454643>
- Simon, H. A. (1996). *The Sciences of the Artificial* (3rd ed.). MIT press.
- Song S, S., & Kim M. (2012). Does More Mean Better? an Examination of Visual Product Presentation in E-Retailing. *Journal of Electronic Commerce Research*, 13(4), 345–355.
- Speier, C., & Venkatesh, V. (2002). The hidden minefields in the adoption of sales force automation technologies. *Journal of Marketing*, 66(3), 98–111. <https://doi.org/10.1509/jmkg.66.3.98.18510>
- Van Aken, J., Berends, H., & van der Bij, H. (2007). *Problem Solving in Organizations: A Methodological Handbook for Business Students*. Cambridge University Press.

- Van Aken, J., & Romme, A. (2012). A Design Science Approach to Evidence-Based Management. *The Oxford Handbook of Evidence-Based Management*, January.
<https://doi.org/10.1093/oxfordhb/9780199763986.013.0003>
- Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, 39(2), 273–315. <https://doi.org/10.1111/j.1540-5915.2008.00192.x>
- Wang, R. Y., & Strong, D. (1996). Beyond accuracy: What data quality means to data consumers. *Journal of Management Information Systems*, 12(4), 5–34.
<https://doi.org/10.1080/07421222.1996.11518099>
- Ware, C. (2019). *Information visualization: perception for design*. Morgan Kaufmann.
- Watson, J., Ghosh, A. P., & Trusov, M. (2018). Swayed by the numbers: The consequences of displaying product review attributes. *Journal of Marketing*, 82(6), 109–131.
<https://doi.org/10.1177/0022242918805468>
- Wohlin, C. (2014). Guidelines for snowballing in systematic literature studies and a replication in software engineering. *ACM International Conference Proceeding Series*.
<https://doi.org/10.1145/2601248.2601268>
- Wunderman, & Thompson. (2019). *De klant van de toekomst*.
<https://insights.wundermanthompsoncommerce.com/nl-future-shopper-rapport>
- Yin, R. K. (2003). Case study research: Design and methods. In *Applied Social Research Method Series* (Issue 5). https://doi.org/10.1300/J145v03n03_07
- Yin, R. K. (2011). *Qualitative Research from start to finish*. The Guilford Press.
- Zumstein, D., & Kotowski, W. (2020). Success Factors of E-Commerce – Drivers of the Conversion Rate and Basket Value. *April*, 43–50. https://doi.org/10.33965/es2020_202005I006

Appendix A – Example of a product detail page (PDP)

1. Philips Hue Filament Lamp - White - A60/E27 - losse lamp - Bluetooth

2. Philips Hue | Serie: Philips Hue Filam 3. ★★★★★ 4,8/5 (125 reviews) | Delen

4.

5.

6. **17,95**
Of bespaar 10% op de stuksprijs als je er 4 koopt

7. **Op voorraad Select**
Voor 22:00 uur besteld, morgen in huis

8. Verkoop door bol.com

Kies je aantal:

1 x € 17,95	2 x € 17,23 € 34,46	3 x € 16,69 € 50,07	4 x € 16,16 € 64,64
	Je bespaart 4%	Je bespaart 7%	Je bespaart 10%

+ In winkelwagen

- ✓ **Gratis** verzending door bol.com vanaf 20 euro
- ✓ Ophalen bij een bol.com afhaalpunt mogelijk
- ✓ 30 dagen bedenktijd en **gratis** retourneren
- ✓ Dag en nacht klantenservice

Bezorgopties op jouw locatie

- ✓ **Vandaag** nog in huis (bestel doordeweeks voor 13:30, bezorging tussen 18:00 en 22:00)
- ✓ Doordeweeks ook 's avonds in huis
- ✓ Ook **zondag** in huis (bestel voor za 23:59)
- ✓ **Vandaag** nog bij afhaalpunt (bestel voor 12:00, ophalen vanaf 17:00)

> Bekijk alle bezorgopties

Shop dit artikel

Bij 2 partners
Verkrijgbaar vanaf € 17,95

Anderen bekeken ook

Philips Hue Slimme Verlichting Filamentlam...	Philips Hue Slimme Verlichting Filamentlam...	Philips Hue Bridge - Slimme verlichting - ...

Led-lamp | E27 | Wattage: 0 | Bediening via mobiele app
> Alle productspecificaties

Bekijk de handleiding

Productbeschrijving

Start al met 1 Hue Bluetooth lamp: draai de Hue-lamp in, download de Hue Bluetooth-app en bedien tot 10 lampen in één ruimte zonder bridge. Breid uit met een bridge om nog meer (of alle) functies te ontdekken die Philips Hue te bieden heeft, zoals het toevoegen tot wel 50 Philips Hue lampen, bedien je lampen ook als je niet thuis bent en blijf altijd up-to-date met de automatische updates.

Makkelijke slimme verlichting

Het vintage ontwerp met de 'ouderwetse' spiraalvormige gloeidraad van deze Philips Hue slimme decoratieve LED-lamp zorgt voor een gezellige.

▼ Toon meer

Productspecificaties

Productspecificaties

Type lichtbron : Led-lamp

Technische specificaties

Figure 29 - Example of a PDP at bol.com

Nr.	PDP element
1.	Product title
2.	Brand name
3.	Review
4.	Image
5.	Video
6.	Price
7.	Availability
8.	Buybox seller
9.	Product description
10.	Specification table

Appendix B – DSS types

Table 18 - Different types of DSS (Power, 2002)

DSS type	Users	Description
Communication-driven	Internal teams	Interactive computer-based system intended to facilitate the solution of problems by decision makers working together as a group
Data-driven	Managers Employees Suppliers	Provides access to and manipulation of large databases of structured data and time-series of internal company and external data
Document-driven	Specialists	Gather, retrieve, classify and manage unstructured documents
Knowledge-driven	Internal users	Specialized problem-solving expertise, consisting of knowledge in a particular domain. Aims to find patterns in a database (data mining)
Model-driven	Managers Employees	Creation and analyzation of accounting-, financial-, representational- and optimization models

Appendix C – Interview format

Interview content quality product detail pages

Name interviewee:

Place: Online Teams Meeting

Name interviewer:

Date and time:

Opening statement

Thank you for participating in this interview. The goal of this interview is to gain insights in the current way of managing the content quality of product detail pages (PDP's) and the need and requirements for a tool to facilitate mass monitoring of PDP elements. The data from this interview will be anonymously processed.

Background information

1. What is your role within the firm?
2. For how long have you been working in in this role?

Main part

Questions regarding the value of online content quality

3. What is the value and the reason for Signify and for you to optimize the PDP content quality for every product in your opinion?
4. What are the intended effects of a PDP with high content quality in your opinion?
5. How important is content management for you and your accounts? Are there differences on the importance of content quality between retailers?

Questions regarding the current method of managing online content

6. Can you describe the current process of content management for online retailers? (i.e. uploading information for new products additions at retailers and managing the PDP's on the quality of the content)
7. Is this process a satisfactory way of working? Why or why not?
 - 7b. If not, what should be changed or created to make it more satisfactory in your opinion?
8. What are the causes of PDP content quality not being optimal for some products in your opinion?
9. Which PDP elements are manageable for your accounts? Are you able to manage these PDP elements for all products for every account?
10. Do you benchmark the content quality for your accounts?

Questions regarding the software tool

11. What can be the added value of designing a software tool to give insights into the status of the PDP content quality for your work and for Signify? Why?
12. What data (i.e. PDP elements) are useful to gain insights to in your opinion?
13. What should a tool, to give insights into the status of the PDP content quality, be able to do in your opinion?
14. What are the user requirements for a tool to give insights into the status of the PDP content quality in your opinion? (e.g. easy to use, easy to understand, info on daily/weekly basis, etc.)
15. Which factors could hinder the use of a tool to give insights into the status of the PDP content quality on different elements?

Appendix D - Data cleaning steps

Table 19 - Overview of data cleaning steps

Data quality dimension	Variable	Reason for adjustment	Solution
Accuracy	Selling price	Format of scraped data was not consistent (different use of “,” and “.” as separators)	Adjust all values automatically with only one separator (“,”)
Accuracy	Bundle product	Self-made bundle products at Coolblue use one identifier for multiple products which leads to assignment of multiple products for one identifier	Make a distinction between bundle-products and normal products with an extra variable “bundle product”
Accuracy	Review score	Format of scraped data was not consistent with format of other values (different use of “,” and “.” as separators)	Adjust all values automatically with only one separator (“,”)
Accuracy	All variables	The scraped data contained duplicate rows	Duplicate rows are deleted by clicking a button

Appendix E – Tool variables

Table 20 - Overview of tool variables

Variable name	Variable location tab	Variable type	Description
<i>% discount</i>	Main data input	General calculation	The discount percentage of a product (inverse of the “Percentage Price deviation” variable)
<i>[Bas] Brand name present</i>	Main data input	Content score calculation	Boolean variable to show if a product has a brand name present or not (1) or not (0)
<i>[Bas] Brand name present in product title</i>	Main data input	Content score calculation	Boolean variable to show if a product has a brand name present in the product title or not (1) or not (0)
<i>[Bas] Image present</i>	Main data input	Content score calculation	Boolean variable to show if a product has an image present (1) or not (0)
<i>[Bas] Product description present</i>	Main data input	Content score calculation	Boolean variable to show if a product has a product description present (1) or not (0)
<i>[Bas] Product name present</i>	Main data input	Content score calculation	Boolean variable to show if a product has a product name present (1) or not (0)
<i>[Bas] Specs table filled</i>	Main data input	Content score calculation	Boolean variable to show if a product has the specification table filled (1) or not (0)
<i>[Ext] 5 or more images present</i>	Main data input	Content score calculation	Boolean variable to show if a product has 5 or more images present on the PDP (1) or not (0)
<i>[Ext] Product with review</i>	Main data input	Content score calculation	Boolean variable to show if a product has at least one review (1) or not (0)
<i>[Ext] Rich content present</i>	Main data input	Content score calculation	Boolean variable to show if a product has rich content present on the PDP (1) or not (0)
<i>[Ext] Video on PDP</i>	Main data input	Content score calculation	Boolean variable to show if a product has a video present on the PDP (1) or not (0)
<i>≥7 days out of stock</i>	Main data input	General calculation	Boolean variable to show if a product has been out of stock for 7 days or more buybox (1) or not (0)
<i>4 or less images</i>	Main data input	General calculation	Boolean variable to show if the product has 4 or less images (1) or not (0)
<i>5 or more reviews?</i>	Main data input	General calculation	Boolean variable to show if the product has 5 or less reviews (1) or not (0)

<i>Basic content score</i>	Main data input	Content score calculation	The calculation of the basic content score
<i>Brand</i>	Main data input, Portfolio Coverage input	Scraping software	The brand name that is used by the retailer
<i>Bundle product?</i>	Main data input	General calculation	Boolean variable to show if the product is a bundle product ("Yes") or not ("No")
<i>Buybox 1/0</i>	Main data input	General calculation	Boolean variable to show if the retailer has the buybox (1) or not (0)
<i>Buybox adjusted</i>	Main data input	General calculation	The adjusted "Seller" variable where all "-" values are replaced with the value "Out of stock"
<i>Covered</i>	Portfolio Coverage input	Scraping software	Boolean variable to show if the product has been found at the retailer (1) or not (0)
<i>Custom group</i>	Main data input	General calculation	Shows if a product is in the custom group EANs tab
<i>Days out of stock</i>	Main data input	Scraping software	The number of days that a product is out of stock, if the product is not out of stock the value is "0"
<i>Download Date</i>	Main data input, Portfolio Coverage input	Scraping software	The date on which the data was scraped from the PDPs
<i>Extended content score</i>	Main data input	Content score calculation	The calculation of the extended content score
<i>Image count</i>	Main data input	Scraping software	The number of images that a product has
<i>In Stock</i>	Main data input	Scraping software	Shows if the product is in stock Y/N
<i>In stock?</i>	Main data input	General calculation	Boolean variable to show if the product is in stock (1) or not (0)
<i>Main category</i>	Main data input	Scraping software	The category that the product is in (category name made by retailer)
<i>MPN</i>	Main data input, Portfolio Coverage input	Scraping software	The MPN code of the product, this is a unique identifier for a product
<i>No video</i>	Main data input	General calculation	Boolean variable to show if the product does not have video (1) or if it does (0)
<i>Percentage Price deviation</i>	Main data input	General calculation	The percentual price difference between the selling price and the RRP
<i>Price deviation</i>	Main data input	General calculation	The absolute price difference between the selling price and the RRP
<i>Price deviation > 15%</i>	Main data input	General calculation	Boolean variable to show if a product has a price deviation of more than 15% compared to the RRP (1) or not (0)

<i>Product Category</i>	Main data input	Signify internal	The category that that the product is in
<i>Product descr present?</i>	Main data input	Scraping software	Shows if the product description is present Y/N
<i>Product EAN/UPC</i>	Main data input, Portfolio Coverage input	Scraping software	The EAN product code, this is a unique identifier for a product
<i>Product name</i>	Main data input, Portfolio Coverage input	Scraping software	The product name as it is in the internal Signify database
<i>Product Page URL</i>	Main data input	Scraping software	The URL link to the PDP
<i>Product status</i>	Main data input	Signify internal	Shows the internal status of a product within Signify (active product, new product introduction, old product (product that is going to be phased out))
<i>Product title</i>	Main data input	Scraping software	The product title that is used by the retailer
<i>Product without any reviews</i>	Main data input	Scraping software	Boolean variable to show if the product has at least one review (1) or not (0)
<i>Retailer</i>	Main data input, Portfolio Coverage input	Scraping software	The name of the retailer
<i>Retailer product ID</i>	Main data input	Scraping software	The product ID that is used by the retailer to identify the product
<i>Review count</i>	Main data input	Scraping software	The number of reviews a product has
<i>Review score <3,5</i>	Main data input	General calculation	Boolean variable to show if a product has a review score less than 3,5 stars (1) or not (0)
<i>Review score adjusted</i>	Main data input	General calculation	The selling review with the adjusted format
<i>Review Score not adjusted</i>	Main data input	Scraping software	The review score that has not been adjusted yet in the right format
<i>Rich content present</i>	Main data input	Scraping software	Shows if rich content is present Y/N
<i>RRP</i>	Main data input	Signify internal	The retailer recommended price of the product
<i>Sell price incorrect format</i>	Main data input	Scraping software	The selling price that has not been adjusted yet in the right format
<i>Seller</i>	Main data input	Scraping software	The name of the seller (e.g. third party sellers), this is the same name as the retailer if the retailer has no marketplace
<i>Selling price</i>	Main data input	General calculation	The selling price with the adjusted format
<i>SL ID</i>	Main data input, Portfolio Coverage input	Scraping software	The identifier that is used by the scraping software

<i>Specs table present</i>	Main data input	Scraping software	Shows if a specification table is present Y/N
<i>Video count</i>	Main data input	Scraping software	The number of videos that a product has
<i>Video location</i>	Main data input	Signify internal	The internal location of the video file for the product
<i>Video title</i>	Main data input	Signify internal	The title of the product video
<i>Yes video</i>	Main data input	General calculation	Boolean variable to show if the product has a video (1) or not (0)

Appendix F – Main datafile from scraping software

Product EAN/UPC	Product name	Retailer name	Sold by	Download Date	Product Page URL	In Stock	Days out of stock	DCC Score	Minimal criteria met	Products without a review	Review Count	Review Score	Image Count	Video Count	Main Category	Selling Price	Product MFR 1	Specs	label is present	Short description present	Product Title	Brand	Rich content present	Shop Product ID	Product ID
8718696129381	Philips Hue Lightstrip Plus basisspaakset V3	Retailer X	Retailer X	3-5-2021	URL	N	0	2	100	0	107	4,6	27	0	ledstrips	44,05	9150006-111	Y	Y	Philips Hue Lightstrip Plus basisspaakset V3	Philips Hue	N	820214	90712	
8718696168151	Philips Hue Lightstrip Plus basisspaakset V3	Retailer X	Retailer X	3-5-2021	URL	N	0	37	100	0	11	4,8	1	0	Philips Hue	240,99	9150006-111	Y	Y	Philips Hue Lightstrip Plus basisspaakset V3	Philips Hue	N	820214	489214	
8718696168151	Philips Hue Lightstrip Plus basisspaakset V3	Retailer X	Retailer X	3-5-2021	URL	N	0	210	0	0	11	4,8	1	0	Philips Hue	107,95	9150006-111	Y	Y	Philips Hue Lightstrip Plus basisspaakset V3	Philips Hue	N	820214	489214	
8718696168151	Philips Hue Lightstrip Plus basisspaakset V3	Retailer X	Retailer X	3-5-2021	URL	N	0	116	0	0	11	4,8	1	0	Smart lampen	222	9150006-111	Y	Y	Philips Hue Lightstrip Plus basisspaakset V3	Philips Hue	N	820214	489214	
8718696168151	Philips Hue Lightstrip Plus basisspaakset V3	Retailer X	Retailer X	3-5-2021	URL	N	0	11	0	0	1	4,8	1	0	Smart lampen	157,99	9150006-111	Y	Y	Philips Hue Lightstrip Plus basisspaakset V3	Philips Hue	N	820214	489214	
8718696168151	Philips Hue Lightstrip Plus basisspaakset V3	Retailer X	Retailer X	3-5-2021	URL	N	0	116	0	0	1	4,8	1	0	Smart lampen	197,95	9150006-111	Y	Y	Philips Hue Lightstrip Plus basisspaakset V3	Philips Hue	N	820214	489214	
8718696168151	Philips Hue Lightstrip Plus basisspaakset V3	Retailer X	Retailer X	3-5-2021	URL	N	0	116	0	0	1	4,8	5	0	Smart lampen	197,95	9150006-111	Y	Y	Philips Hue Lightstrip Plus basisspaakset V3	Philips Hue	N	820214	489214	
8718696168151	Philips Hue Lightstrip Plus basisspaakset V3	Retailer X	Retailer X	3-5-2021	URL	N	0	116	0	0	20	4,3	10	0	Verlichting	13,59	9290294-111	Y	Y	WZ Lampe E27 6W WZ	WZ	N	1670657	3366599	
8718696168151	Philips Hue Lightstrip Plus basisspaakset V3	Retailer X	Retailer X	3-5-2021	URL	N	0	116	0	0	1	4,1	10	0	Verlichting	17,99	9290294-111	Y	Y	WZ Lampe G635 WZ	WZ	N	1670654	3366601	
8718696168151	Philips Hue Lightstrip Plus basisspaakset V3	Retailer X	Retailer X	3-5-2021	URL	N	0	116	0	0	1	4,1	10	0	Verlichting	14,59	9290294-111	Y	Y	WZ Flouwerlam WZ	WZ	N	1670653	3366627	
8718696168151	Philips Hue Lightstrip Plus basisspaakset V3	Retailer X	Retailer X	3-5-2021	URL	N	0	116	0	0	9	3,9	10	0	Verlichting	14,59	9290294-111	Y	Y	WZ Flouwerlam WZ	WZ	N	1670652	3366628	

Figure 30 - Main datafile from scraping software

Appendix G – Initial design: retailer dashboard

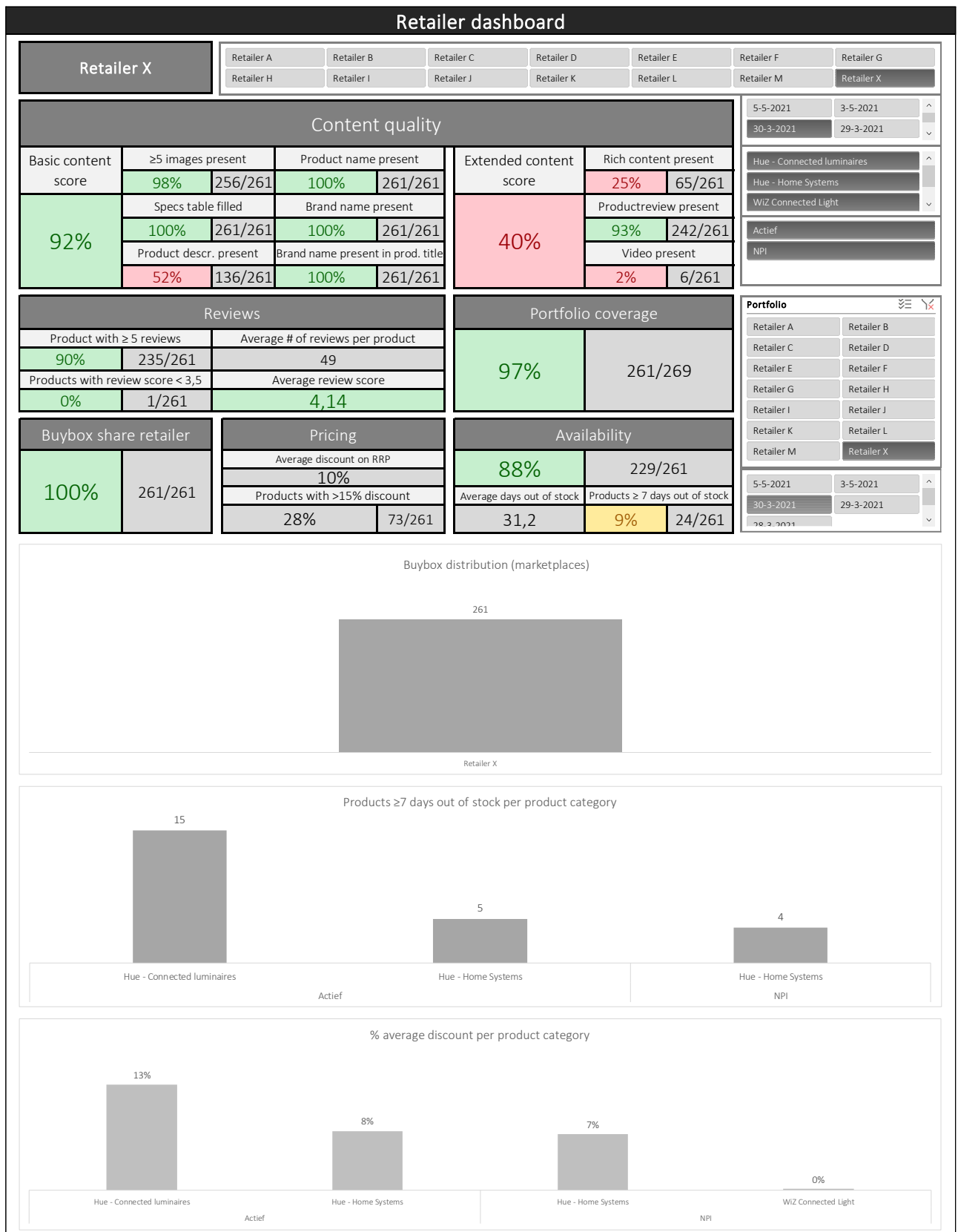


Figure 31 - Initial design complete retailer dashboard

Appendix H – Initial design: overall dashboard (1)

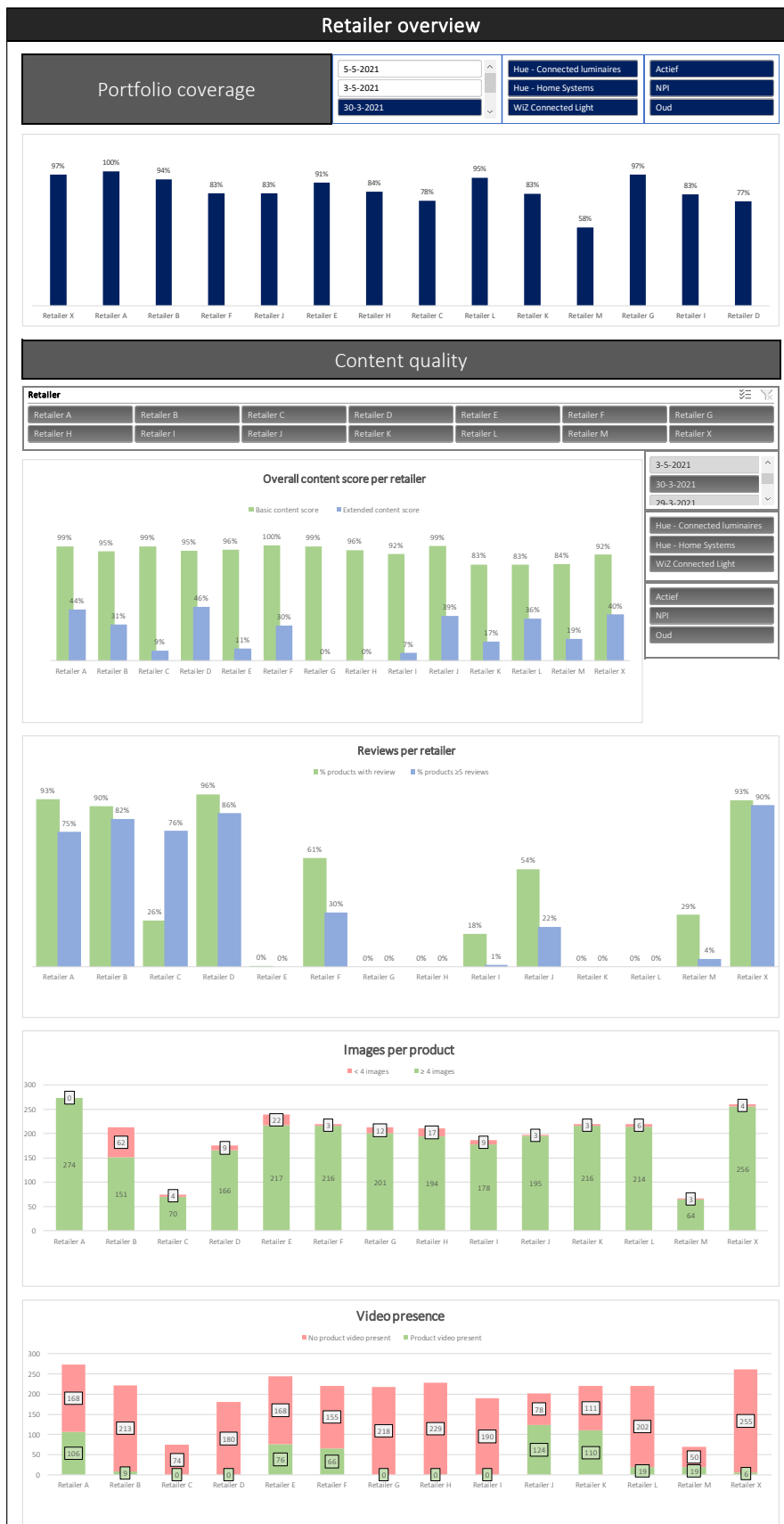


Figure 32 - Initial design complete overall dashboard (1/2)

Appendix H – Initial design: overall dashboard (2)



Figure 33 - Initial design complete overall dashboard (2/2)

Appendix I – Drill-down tabs overview

Table 21 - Overview of drill-down tabs in dashboard

Tab name
Basic content score
Extended content score
Pricing
Availability
Portfolio Coverage
Products without buybox
Specs table filled
Product descr. present
Image present
Rich content present
Product name present
Brand name present
Brand name present in in title
Review present
≥5 images present
Video present
Review score <3,5

Appendix J – SUS score

Questions:

1. I think that I would like to use this product frequently
2. I found the product unnecessarily complex
3. I thought the product was easy to use
4. I think that I would need the support of a technical person to be able to use this product
5. I found that the various functions in this product were well integrated
6. I thought that there was too much inconsistency in this product
7. I would imagine that most people would learn to use this product very quickly
8. I found the product very awkward to use
9. I felt very confident using the product
10. I needed to learn a lot of things before I could get going with this product

The final SUS score is calculated as follows:

- For each of the odd numbered questions, subtract 1 from the score.
- For each of the even numbered questions, subtract their value from 5.
- Add up these values and multiply this by 2.5 to get the SUS score.

Appendix L – Solution design: Retailer dashboard

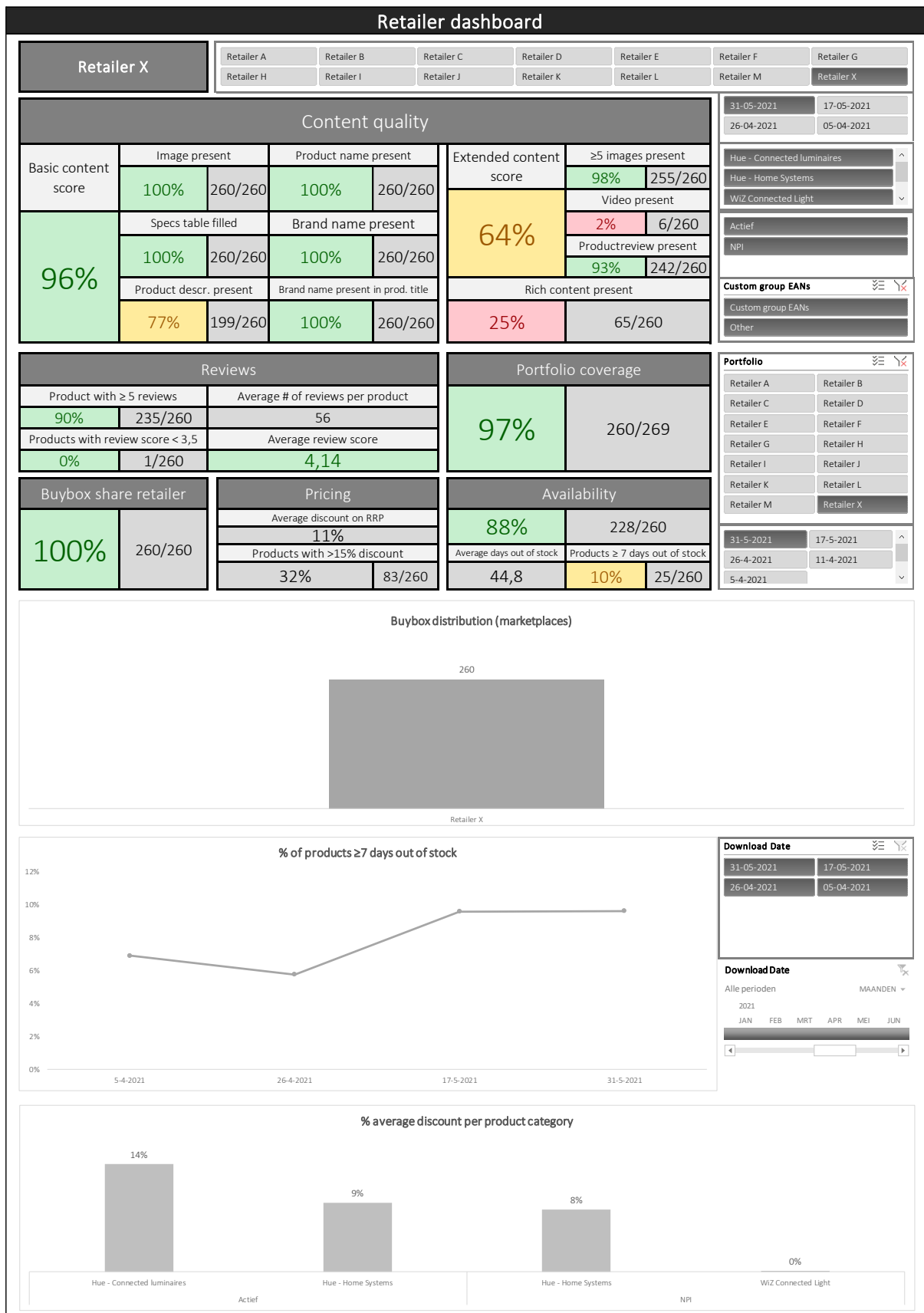


Figure 34 - Final solution design retailer dashboard