The Data Driven Decision RACE in eRetailing

Niklas Eriksson
Department of Business Management and Analytics
Arcada University of Applied Sciences
Helsinki, Finland
Email: niklas.eriksson@arcada.fi

Mikael Forsström
Department of Business Management and Analytics
Arcada University of Applied Sciences
Helsinki, Finland
Email: mikael.forsstrom@arcada.fi

Carl-Johan Rosenbröijer
Department of Business Management and Analytics
Arcada University of Applied Sciences
Helsinki, Finland
Email: carl-johan.rosenbroijer@arcada.fi

Abstract

This study takes a customer centric approach to investigate small eRetailers' data driven decisions. The research is based on an edited version of Chaffey and Smith´s (2013) RACE framework and an edited version of the business analytics framework by Delen and Demirkan (2012a), divided in knowledge and data driven decision-making. By combining these two frameworks we create the Data Driven Decision RACE model. The empirical research is a survey among small Finnish eRetailers. The findings indicate that a majority of the studied eRetailers do analyze data and understand customer online behavior especially in the Reach and Engage stages of the Data Driven Decision RACE model. However, the study also indicates that the data driven decision-making is fairly low within all three stages of the model, which implies that small eRetailers primarily rely on experience and gut instinct rather than on customer data when they make decisions concerning their online activities.

Keywords business analytics, big data, data driven decision-making, eRetailing

1 Introduction

Big Data and analytics is seen as a very critical area in business when it comes to future decision-making (see e.g. Brynjolfsson and McAfee 2012; Davenport 2014). The trend seems to be that data driven decision-making is not only more trustworthy than intuition and experience based decision-making, but also results in better performance for companies. The digitalization of business and especially the Internet infrastructure has led to the creation of enormous amounts of data that can be accessed openly, in real-time and collected for advanced analytics.

The eRetailing context is highly digital, which makes it interesting from a big data and analytics perspective. There is a continuous flow of data created as a result of customers' activities in e.g. search engines, social media, blogs, Web sites and online shops. All this data can be part of data driven marketing decisions that preferably end with a purchase and customer advocacy. There are two current trends in retail, the omnichannel phenomena and the rapidly developing mobile commerce (Wojciech and Cuthbertson 2014; Pousttchi et al. 2015). Both trends are driven by information and communication technology (ICT), and especially the development and increasing popularity of smartphones. The omnichannel phenomena is blurring the border between the physical brick-and-mortar and the online store. Mobile commerce entails a vast amount of digital activities that the consumer can engage in while shopping virtually anywhere 24/7, e.g. searching for information, reading customer reviews, posting on social media, sharing pictures of products, buying online etc.

Of 16 – 89 years old Finns 62% have made purchases online during the past three months (Official Statistics of Finland 2015). eCommerce in Finland has grown constantly, and in 2014 consumers bought products and services online for a value of €10,5 billion (TNS Gallup 2015). The proportions of the total online sales were services 54 %, products 45 % and digital content 1 %. However, according to a survey from 2015 the Finnish eRetailers are usually quite small and homespun and a major part of the online sales are going to major foreign eRetailers (Verkkoteollisuus 2015).

As there is constant access to data in an eRetailer context it becomes critical to see if this data is collected, used and analyzed for decision-making. Referring to previous research (Brynjolfsson et al. 2011; Germann et al. 2013), we assume that data driven decision-making increases company performance. Hence, we see a need to investigate how advanced eRetailers are in data driven decision-making.

Against this background, the aim of this study is to use a customer centric approach to better understand small eRetailers' data driven decisions. A central part of the aim is to develop a Data Driven Decision RACE model based on the customer centric RACE model by Chaffey and Smith (2013) and literature regarding data driven decision-making. The empirical study aims at answering to what extent small eRetailers analyze Web data, how well and precisely small eRetailers understand online customers in the different phases of the Data Driven Decision RACE model and how systematically, diversely and continuously small eRetailers use data and analytical techniques to make decisions and take actions in the different phases of the model.

2 Literature Review and Model

2.1 Data Driven Decision-making

Delen and Demirkan (2012b) argue that the main job of the managers, decision-making, becomes more complex, and to repeatedly making the right decisions in a timely manner becomes a matter of survival. Data is the key building block for decision-making. The quality and accuracy of data becomes crucial for successful decision-making. With the Internet infrastructure and digital revolution we have seen an explosion of sites, e.g. Web sites, eCommerce platforms, search engines and social media platforms (for more see Chaffey and Smith 2013). The global and local traffic on these sites create a continuing flow of what we call big data on a 24/7 basis. The institutionalized definition of big data is high volume, high velocity and high variety data (META Group/Gartner). Another feature of big data is that it is real-time. This makes it possible to collect data and analyze it continuously. Davenport (2014) presents a development of terminology concerning using and analyzing data between 1989 and present time; (1) Business intelligence (1989-2005) with tools to support data driven decision-making with emphasis on reporting, (2)Analytics (2005-2010) based on statistical and mathematical analysis for decisions and (3) Big data (2010-present) focusing on very large, unstructured and fast moving data. All of these eras have in common a data driven decision-making philosophy. Big data is also very much related to the upcoming trend of data-enriched service innovation (Davenport 2013) and to marketing analytics in retail (German et al. 2013).

General categorizations of elements needed for data driven decision-making are data, information and knowledge. Data is for example numbers, text, and/or graphics (e.g. pictures and videos) without any context. To become information, data has to be placed in a certain context or system. For information to become knowledge it has to be analyzed. The knowledge level is often related to analytics, i.e. statistical and mathematical analysis of data. Delen and Demirkan (2012a) present a development of service oriented decision support systems where data-as-a-service and information-as-a-service are already established whereas analytics-as-a-service is a relatively new concept in the business world. The analytics-as-a-service concept is based on the increased popularity of business analytics as a managerial paradigm. The same authors divide business analytics into descriptive, predictive and prescriptive analytics. Descriptive analytics focuses on answering questions like what happened and what is happening, enabling data driven business reporting and dashboards. Whereas predictive analytics is future oriented, i.e. questions like what will happen and why it will happen are critical, enabling e.g. data mining, Web-mining and forecasting. Finally, the prescriptive analytics approach is normative in nature and aim at answering “what should I do and why should I do it?”, enabling e.g. simulation and optimization. All three perspectives aim at outcomes that enable the decision-maker to make data based decisions increasing business performance.

In an online retail setting the analytics-as-a-service concept has been referred to as Web-analytics. Web-analytics is a technique used to assess and improve the contribution of digital marketing to a business including reviewing traffic volume, referrals, click-streams, online reach data, customer satisfaction surveys, leads and sales (Chaffey and Smith 2013). Google Analytics is a very popular cloud based web analytics service. The service tracks online traffic and contributes to insights on online customer behavior i.e. concerning building an audience for offerings and the conversion to sales. It also offers descriptive analytics in the form of dashboards. The question whether this is collected data used for data driven decision-making and taking customer centric actions remains.

Brynjolfsson et al. (2011) argue that the managerial decisions of a growing amount of companies rely less on the “gut instinct” of the leader than on data based analytics. Retailers would clearly benefit from decision-making based on customer analytics due to the fact that they make many of the same decisions repeatedly. Germann et al. (2014) also see clear advantages with customer analytics based decision-making in retail because retailers have access to a large volume of customer data, powerful customer analytics methods tailored to retailers are available and customer analytics based methods exist for many retailing decisions that are made on a regular basis. As a result of the increased amount of data available, a trend has emerged where leading edge firms have moved from passively collecting data to actively conducting customer experiments to develop and test new products and services (Brynjolfsson et al. 2011). This culture of experimentation has diffused to e.g. pure online retailers, like Amazon and Zalando. These types of online firms rely heavily on field experiments, utilizing high visibility and high volume of online customer interaction to validate and improve new product and pricing strategies (Brynjolfsson et al. 2011).

2.2 A Customer Centric Approach

The customer centric approach used in this study is edited from Chaffey and Smith´s (2013) PRACE framework. Here we will use the framework as a RACE model (R=Reach, A&C=Act and Convert, E=Engage), hence the first P=plan will not be in focus because it takes a more strategic approach where planning becomes important. Instead our approach is based on a more operational level. The structure is a customer focused behavioral process that we divide in three buyer stages (originally four). Each buyer stage has a management goal, i.e. related to the RACE framework.

1) Exploration – Reach

First the customer is in an exploration stage where he/she is exploring alternatives or only out of interest search for product information, reviews (technical or user based), tests, discussions etc. This can be done through search engines, social networks, publishers, blogs etc. Here the management goal is Reach, i.e. how can we reach the potential customers and building awareness of our brand and its products or services. The main aim of reaching the right customers with the right message need to lead to traffic to our own home site, social media site, blog and/or eCommerce site. To be able to assure that the Reach goal is achieved and create traffic to our main content sites, we need data and analytics. We also need some sort of measures, e.g. number of fans, followers, visitors, inbound links etc.

2) Decision-making and Purchase – Act & Convert

In this buyer stage the customer has already reached our home site, blog and/or social media community. The customer is here in the decision-making process, i.e. should I buy or not, what should I buy, etc. The management goal here is to get the customer to act, hence to get the customer to find out more of the company and its products or services. Data is here measured as e.g. time on site, shares, comments, likes, leads and conversion. With the management goal convert the main aim is to get the customer to purchase a product and/or service. Then the management has reached its commercial objective. In this buyer stage, data is crucial because it measures the commercial success of the eRetailer. The measures can then be orders, revenue, average order value, etc.

3) Advocacy – Engage

In this last stage the customer has purchased, hence become a customer. Here it is crucial to engage the customer to share their experiences of the process, product and/or service. The aim is to build a deeper customer relationship encouraging advocacy or recommendations through word-of-mouth/mouse. In this stage data is measured by for example repeat purchase, referral, etc.

Data can also be used to personalize and enhance the customers' searching and navigating capabilities on a personal level (Davenport 2013; Kaptein and Parvinen 2015). Recommendations can also be launched during an online session so that the customer can be offered complementing products (cross-sell) or higher value products (up-sell). With good quality and detailed data, the customer can be offered a personalized support experience. Especially in the first Reach stage and the third Engage stage, customer reviews and recommender systems become a central issue that clearly has an impact on the consumer behavior (see e.g. Baum and Spann 2014; Gensler et al. 2015). Collecting data and understanding this phenomenon becomes crucial in being able to make data driven decisions and react to customers in the RACE stages.

The edited customer centric approach is then combined with the data driven decision-making approach to a model that we refer to as the Data Driven Decision RACE model.

2.3 The Data Driven Decision RACE Model

According to the first aim of this study, we create a model that combines data driven decision-making (2.1) with the customer centric approach (2.2) (see Figure 1). The data driven decision-making presented above was divided in two areas; knowledge and data driven decision-making. In our model the starting point is analyzing data. This is a prerequisite to be able to make data driven decisions. The "knowledge" measures the level of eRetailers' understanding of why the customers behave in certain ways in the online context. The "data driven decision-making" measures the level of the eRetailer's use of data and analytical techniques to make decisions and take actions concerning online activities.

The customer centric approach is based on three buyer stages; exploration, decision-making & purchase and finally advocacy. From an eRetailer perspective the management goal is to Reach, Act & Convert and finally to Engage. These three goals are giving the main structure of the created Data Driven Decision RACE model. See Figure 1.

Reach (R)	
Knowledge Understanding online customer behavior	Data Driven Decision-making Using data and analytical techniques for decisions and actions
Act & Convert (AC)	
Knowledge Understanding online customer behavior	Data Driven Decision-making Using data and analytical techniques for decisions and actions
Engage (E)	
Knowledge Understanding online customer behavior	Data Driven Decision-making Using data and analytical techniques for decisions and actions

Figure 1: The Data Driven Decision RACE model

2.4 Research Questions

Building on the preceding discussion, the aim of this research and the presented Data Driven Decision RACE model, we address the following four research questions:

- RQ1: To what extent are small eRetailers analyzing data?
- RQ2: How well and precisely do small eRetailers understand their customers' and visitors' online behavior in the different phases of the customer centric Data Driven Decision RACE model?
- RQ3: How systematically, diversely and continuously do small eRetailers use data and analytical techniques to make decisions and take actions in the different phases of the Data Driven Decision RACE model?
- RQ4: Is there a relationship between the type of eRetailer (online sales of turnover) and how they understand online customers and use data to make customer centric decisions?

The last research question was raised in order to identify if eRetailers' online sales of total turnover is a driver for making customer centric decisions based on data. It seems logical that retailers primarily operating online are the ones to take the most advantage of data in their customer centric decisions.

3 Method

3.1 Data Collection Procedures

Based on the aim of the study we conducted a survey among small eRetailers in Finland. The sample consists of small eRetailers that either operate only online or both online and offline, i.e. with one or several brick-and-mortar stores. The questioner was sent to 1300 small Finnish eRetailers. They are all customers of Vilkas Oy (www.vilkasgroup.com) and use ePages, a cloud based eCommerce service platform. About a third of active Finnish Web shops are based on the platform of Vilkas Oy, which makes Vilkas Oy the market leader in Finland for eCommerce platforms. An online questionnaire was created with the QuestionPro tool and sent per email to the respondents in November 2015. In total 101 respondents completed the questionnaire, yielding an effective response rate of 7.8%. The email-addresses that were used are assigned to persons responsible for the eRetailers Web shop(s). Hence, the 101 respondents are persons who should be knowledgeable about their companies' online activities and data analytics. They responded to a questionnaire that started with company profile data and general questions regarding data analytics in the company (see Table 1 and 2). Then they answered three sections with statements according to the phases in the data driven decision RACE model; (1) Reach, (2) Act & Convert and (3) Engage (see Table 3). As this is the first attempt to operationalize the data driven decision RACE model, we needed to develop statements to represent each phase in the model. The statements were developed according to the literature discussed above and by consulting a group of analytics experts. We also pre-tested the questionnaire with our partner, Vilkas Oy. Based on their comments and suggestions we improved the questionnaire and we also decided to use three statements for each category in the model. The three statements are designed to represent a construct in the model (see Table 3). We also included concrete examples in the statements to increase the reliability. The survey was conducted in Finnish and the statements have been translated from Finnish to English in this paper.

3.2 Descriptive Statistics of the Sample

Table 1 shows that of the eRetailers that participated in the survey, 68.3% have been founded in the last five years (2011-2015), whereas 28.7% were founded before 2011. A minority 36.6% had one or more brick-and-mortar stores parallel to their online shop. Around half of the companies 52.5% had an annual turnover under 50 000 € and 57.4% reported that the proportion of online sales represented 50 % or more of their total turnover. Very few of the participating companies have reached an international market, as many as 84.2% of the companies estimated that the share of international sales represented at most 1% of their annual turnover. The eRetailers sell a wide range of different products and hence the sample represent many product categories within retail. The participants' customers are primarily within the B2C sector (71.3%). Based on the descriptive statistics we can say that the sample primarily represents quite young and small Finnish B2C eRetailers focusing on the Finnish market, which is quite typical for Finnish eRetailers (Verkkoteollisuus 2015).

	Sample N = 101
Web shop founded	< 2011 28.7% (29) 2011 - 2015 68.3% (69) Missing 3% (3)
Brick-and-mortar store(s)	No 63.4% (64) Yes, one or more 36.6% (37)
Turnover annually	< 50.000 € 52.5 % (53) >= 50.000 € 47.5% (48)
International trade of annual turnover	=< 1% 84.2% (74) > 1% 15.8% (27)
Primary customers of the Web shop	B2C 71.3% (72) B2B 5.9% (6) Both 22.8% (23)

Table 1. Profile of the sample eRetailers

4 Results

We will here present the results according to the four research questions raised.

RQ1: To what extent are small eRetailers analyzing data?

Many of the companies (64.35%) reported that the frequency of analyzing data was done systematically at least once a month and 36 companies (35.65%) did so less frequently or not at all. Most of the companies (82.17%) reported that they had taken a web analytics tool in use (e.g. Google Analytics, Snoobi, etracker) and 18 (17.82%) reported that they did not follow up traffic data in their Web shop with a Web analytics tool. 59 (58.41%) of the companies reported that Web analysis is mainly carried out by an internal dedicated expert. Only 8 companies (7.92%) relied on a dedicated external expert. As many as 34 (33.66%) reported that they had no dedicated expert to take care of Web and data analysis.

	Sample N = 101
Web-analytics tool in use (Google Analytics, Snoobi, other)	Yes 82.17% (83) No 17.82% (18)
Dedicated Web- and data-analytics expert	Internal 58.41% (59) External 7.92% (8) None 33.66% (34)
Frequency of analyzing data	Every day 7.9% (8) Every week 28.7% (29) Every month 27.7% (28) Less 18.8% (19) Never 16.8% (17)

Table 2. To what extent are eRetailers analyzing data?

RQ2: How well and precisely do small eRetailers understand their customers' and visitors' online behavior in the different phases of the customer centric Data Driven Decision RACE model?

The data was collected based on a five point Likert-scale ([5] strongly agree – [1] strongly disagree) for each statement in the model. In Table 3 we can see mean values, standard deviation and percentages of the different statements according to Reach, Act & Convert and Engage and according to Knowledge and Data Driven Decision-making. Instead of using skewness as a measure of asymmetry we used a simple percentage, describing the percentage of respondents who answered [5] strongly agree or [4] agree for each statement out of 101 respondents. We will first focus on the percentages in the analysis to see to what extent the participants agree with the statements.

Table 3 shows that a majority (>50%) of the responding eRetailers agree to that they have the knowledge how to Reach online customers and visitors; they understand why visitors reach their Web shop (63.4%), where the most profitable customers come from (54.5%) and what type of social media activities generate the most traffic to the Web shop (50.5%). A clear majority also report that they understand how to Engage with their customers online; they understand how product/service discussions (e.g. in social media) affect sales (73.3%), what kind of communication with customers (e.g. newsletters, online chat) increases sales (61.4%) and what affects customer retention of the Web shop (64.4%). However, a minority (<50%) of the participating eRetailers agree that they understand how to Act & Convert online customers, visitors; they understand how visitors from different sources behave in the Web shop (37.6%), fully why they lose customers in different stages of the order process (24.8%) and how different key performance indicators should be interpreted (42.6%).

We also summed the mean scores of the three statements for each construct and calculated an average mean score (see Table 4). In the case of Knowledge, the average means of the three statements in Reach (average mean = 3.43) and Engage (average mean = 3.62) are clearly above the average mean of the three statements in Act & Convert (average mean = 2.84). According to Cronbach's alfa in Table 4 the internal consistency of the statements in the three Knowledge constructs are also on good level (all three > 0.8).

RQ3: How systematically, diversely and continuously do small eRetailers use data and analytical techniques to make decisions and take actions in the different phases of the Data Driven Decision RACE model?

The right column in Table 3 shows that a minority (<50%) of the responding eRetailers make data-driven decisions and take actions according to the three phases of our model; Reach, Act & Convert and Engage. None of the rated statements are above 50%. The highest percentages are in the Reach phase; continuously use data in Web-analytics to target marketing activities (41.6%), continuously perform campaign tests to launch effective campaigns (35.6%) and most often use data from Web-analytics to update our online ads during campaigns (31.7%). Also the Engage phase shows relatively high percentages; use different techniques to ensure that customers can share information about our products (41.6%), always send targeted messages to customers after purchase (33.7%) and frequently use different techniques to personalize customer communication (26.7%). The lowest percentages are found in Act & Convert, the single lowest percentage was 9.9% for systematically conduct tests (e.g. A/B tests, usability tests) to improve conversion. The average means in Table 4 of the three statements for each Data Driven Decision-Making construct follow the same pattern as for the individual statement percentages. Both the individual statement percentages and the average means of the constructs are also clearly lower for Data Driven Decision-Making than for Knowledge. The internal consistency of the statements in the three Data Driven Decision-Making constructs are also on good or acceptable level (Cronbach's alfa exceed at least 0.7).

In our further analysis, we analyzed the bivariate correlation of the average means of all the constructs. The correlation showed a clear significant relationship between Knowledge and Data Driven Decision-Making. The Pearson correlation score for the Reach constructs was 0.664 (sig. 0.000), the Act & Convert constructs 0.701 (sig. 0.000) and Engage constructs 0.552 (sig. 0.000). The positive correlations indicate that better understanding of online customers is linked to more systematic, continuous and diverse use of data and analytical techniques for customer-centric decisions among the responding eRetailers.

RQ4: Is there a relationship between the type of eRetailer (online sales of turnover) and how they understand online customers and use data to make customer centric decisions?

As shown in the histogram in Figure 2 we have a wide distribution of online sales of turnover (1% - 100%) among the 101 participating eRetailers. 43 eRetailers represent firms with a turnover mainly offline (<50% online sales of turnover) and 58 eRetailers represent firms with a turnover mainly online (>= 50% online sales of turnover). We run a bivariate correlation analysis to investigate the relationship between online sales of turnover (estimated %) and the average means of the constructs (see Table 5.). The eRetailers with more online sales of total sales report higher average mean scores for all three stages of the Data Driven Decision RACE model. All correlation scores in Table 5 for Online sales (%) are positive for the six constructs. The results show significant correlation for the Reach stage and Engage stage of the model, both regarding Knowledge and Data Driven Decision-Making. However, in the Act & Convert stage the correlation results do not show significant correlation for Knowledge and neither for Data Driven Decision-Making.

	Knowledge statements	Mean*	St. Dev.	%**	Data Driven Decision-Making statements	Mean*	St. Dev.	%**
Reach	We have a good understanding of why customers reach our Web shop from different sources.	3.56	1.17	63.4	We continuously use data in Web-analytics to target marketing activities.	3.05	1.24	41.6
	We understand where the most profitable customers come from (e.g. via bought, earned or owned media).	3.42	1.16	54.5	We most often use data from Web-analytics to update our online ads during campaigns	2.80	1.25	31.7
	We understand what type of activities in our social media channels generate the most visitor traffic to our Web shop.	3.31	1.13	50.5	We frequently test our online campaigns to be able to launch the most effective one.	2.88	1.28	35.6
Act & Convert	We have a good understanding of how customers from different sources behave in our Web shop.	2.97	1.21	37.6	We continuously use different techniques to personalize the shopping experience (e.g. by suggesting previously viewed products to returning customers)	2.63	1.43	29.7
	We understand fully why we lose customers in different stages of the order process.	2.56	1.19	24.8	We have highly automated processes that enable cross- and up-selling.	2.63	1.32	31.7
	We have a good understanding of how different key performance indicators should be interpreted (e.g. conversion rate, average order value)	2.99	1.25	42.6	We systematically conduct tests (e.g. A/B tests, usability tests) to improve conversion.	1.95	1.08	9.9
Engage	We have a good understanding of how discussion (e.g. in social media) about our products/services affect sales.	3.78	1.05	73.3	We frequently use different techniques to personalize customer communication (e.g. reminder emails of abandoned shopping carts)	2.53	1.25	26.7
	We have a good understanding of what kind of communication with our customers (e.g. newsletters, online chat) increases sales.	3.54	1.11	61.4	We always send targeted messages after purchase to our customers (e.g. ask customers to rate our products).	2.71	1.40	33.7
	We have a good understanding of what affects customer retention of the Web shop.	3.55	1.07	64.4	We use different techniques to ensure that customers can share information about our products (e.g. share tools in newsletters and Web shop).	2.97	1.28	41.6

* Scale: [5] Strongly agree, [4] Agree, [3] Neutral, [2] Disagree, [1] Strongly disagree

** The percentage of respondents answering strongly agree or agree for each statement out of 101 respondents

Table 3. Knowledge and Data driven decision-making in the different phases of the Data Driven Decision RACE model

Knowledge	Average Mean*	St. Dev.	A	Data Driven Decision-Making	Average Mean*	St. Dev.	α
Reach	3.43	1.05	0.895	Reach	2.91	1.13	0.883
Act & Convert	2.84	1.07	0.857	Act & Convert	2.41	1.12	0.849
Engage	3.62	0.95	0.857	Engage	2.74	1.07	0.751

* A calculated average mean score based on the mean scores of the statements, scale: [5] Strongly agree, [4] Agree, [3] Neutral, [2] Disagree, [1] Strongly disagree

Table 4. Average means of statements for each construct and Cronbach's alfa

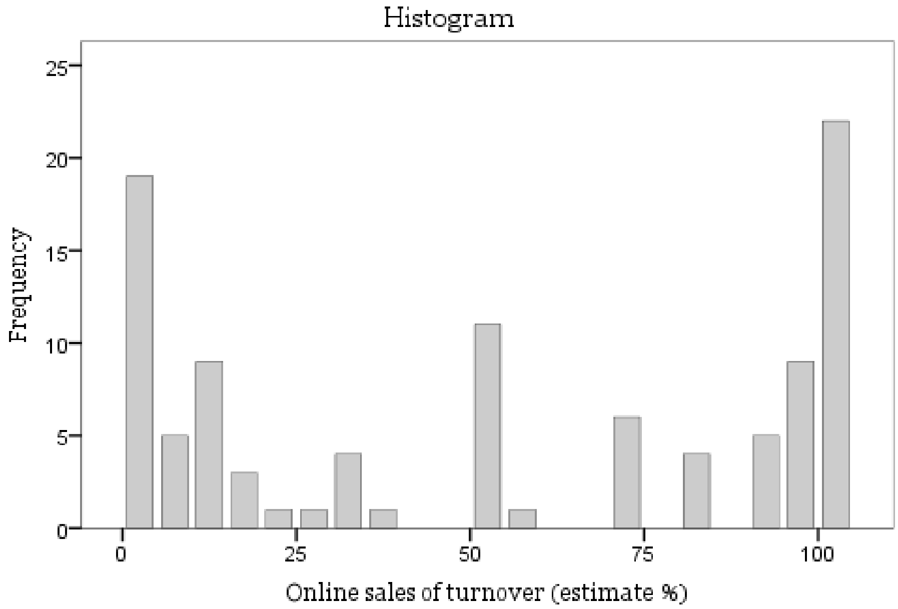

Figure 2. Distribution of the eRetailers' online sales of turnover (estimate %)

		Online sales of turnover (estimate %)	Knowledge: Reach	Knowledge: Act & Convert	Knowledge: Engage	Data Driven Decision-Making: Reach	Data Driven Decision-Making: Act & Convert	Data Driven Decision-Making: Engage
Online sales of turnover (estimate %)	Pearson Correlation	1	0.207*	0.157	0.420**	0.229*	0.146	0.235*
	Sig. (2-tailed)		0.038	0.118	0.000	0.021	0.145	0.018

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

Table 5. Correlation between online sales of turnover and average means of the constructs

5 Discussion

The first aim of this study was to create a model, called, the Data Driven Decision RACE model. The processual structure of the eRetailer's three stages and related goals is based on our edited version of Chaffey and Smith's (2013) framework, which is designed to guide the eRetailer when implementing a digital strategy. The focus is on tactics, action and control. Our approach is mainly related to control, i.e. performance measurement against detailed targets. The created model contributes to the challenge of collecting, analyzing and using data for decision making and taking customer centric actions. The model can be used as a tool to analyze the eRetailer's capability of understanding the customers' online behavior in different stages of the model. The model gives indication of the use of data and analytical techniques for decision-making. We see that the Data Driven Decision RACE model is a conceptual contribution and tool which here has been operationalized in this survey research.

The second aim of this study was to better understand, based on empirical data, to what extent small eRetailers analyze Web data, how well and precisely small eRetailers understand online customers in the different phases of the Data Driven Decision RACE model and how systematically, diversely and continuously small eRetailers use data and analytical techniques to make decisions and take actions in the different phases of the model.

Based on the empirical results it seems like a majority of the responding eRetailers analyze data systematically at least monthly and they report to have a relatively good understanding of their online customers and visitors in the Reach and Engage stages of the model. Most of the investigated eRetailers also have an analytics tool in use and a majority have a dedicated internal or external Web and data analytics expert. Nevertheless, it should be noted that there are eRetailers that do not analyze data, do not have analytical tools installed, do not use dedicated analytics experts and agree that they have a limited understanding of their online customers and visitors.

Furthermore, only a minority of the investigated eRetailers seem to make systematic, diverse and continuous data-driven decisions according to the different stages (RACE) in the model. It also seems evident from the results that the second phase Act & Convert is the main challenge for the eRetailers. This is interesting, as all factors are considered, conversions and actual sales are what drive revenues. It should also be noted that there is a clear positive relationship between Knowledge, as understanding online customer behavior, and Data Driven Decision-Making. This result indicates a clear knowledge enhancement among the eRetailers who use data and analytical techniques in customer-centric decision-making.

Further analysis also shows that eRetailers with mainly online sales are primarily the ones that make decisions and take actions based on data according to the Data Driven Decision RACE model. This is logical as these eRetailers' core business activities are online. However, the results also reveal that these eRetailers find the Act & Convert stage of the Data Driven Decision RACE model to be the most undeployed, both regarding understanding how to convert online activities into sales and actually make systematic and continuous decisions to achieve conversions. The correlation results showed that the average mean values for the Act & Convert phase were not significantly higher for eRetailers with mainly online sales than for eRetailers with mainly offline sales.

6 Conclusion

In this study we have presented the Data Driven Decision RACE model. The model was operationalized and used to investigate four different research questions regarding eRetailers' data driven decision-making. The empirical findings show that a majority of the investigated small eRetailers do analyze data, have analytical tools installed, use dedicated analytics experts and they, in fact, report to have a reasonably good understanding of their online customers and visitors. However, only a minority of the investigated eRetailers seem to make systematic, diverse and continuous data-driven decisions according to the three phases in our model. This implies that the small eRetailers primarily rely on experience and gut instinct rather than on data analytics when they make decisions and take actions concerning their online activities. Especially the Act & Convert phase of the RACE model seems to be challenging for the investigated eRetailers. However, small eRetailers that have a better understanding of online customer behavior also report making more data driven decisions. Finally, it seems like eRetailers with mainly online sales are the precursors of the Data Driven Decision RACE for small eRetailers in Finland.

Although we believe that we have contributed with new aspects with this study, there are limitations. First our sample is based on Finnish small eRetailers, limiting this study primarily to a Finnish context. Therefore, extensive cross-border studies and samples also with larger eRetailers should be valuable to conduct. Secondly, our developed statements in the model are measured based on perceptual responses by a key person from each participating eRetailer and not on an objective evaluation of the eRetailers. Thirdly, the Data Driven Decision RACE model could be further developed. By adding a layer of eRetailer performance indicators we see that it is possible to construct a casual effect model to measure the impact of customer centric data driven decisions on small eRetailers performance. On the other hand, as noted there is a growing body of research indicating that investments in data and marketing analytics do increase Retailer performance (Germann et al. 2013; Germann et al. 2014).

7 References

Brynjolfsson, E., Hitt, M.L. and Kim, H.H. 2011. "Strength in Numbers: How Does Data-Driven Decision Making Affect Firm Performance?," *Social Science Research Network*, 22 April, 2011, DOI: http://dx.doi.org/10.2139/ssrn.1819486 Retrieved 29 March, 2016.

Baum, D. and Spann, M. 2014. "The Interplay Between Online Consumer Reviews and Recommender Systems: An Experimental Analysis," *International Journal of Electronic Commerce* (19:1), Fall, pp 129-162.

Chaffey, D. and Smith, P.R. 2013. *Emarketing Excellence – Planning and Optimizing Your Digital Marketing*. 4th edition New York: Routledge.

Davenport, T. H. 2013. "Analytics 3.0," *Harvard Business Review*, December 2013, pp 64-72.

Davenport, T. H. 2014. "Big Data @ Work – Dispelling the Myths, Uncovering the Opportunities," *Harvard Business School Publishing Corporation*, USA.

Delen, D. and Demirkan, H. 2012a. "Data, Information and Analytics as Services," *Decision Support Systems* (55:1), pp 359-363.

Delen, D. and Demirkan, H. 2012b. "Leveraging the Capabilities of Service-Oriented Decision Support Systems: Putting Analytics and Big Data in Cloud," *Decision Support Systems* (55:1), pp 412-421.

Gensler, S., Völckner, F., Egger, M., Fischbach, K. and Schoder, D. 2015. "Listen to Your Customers: Insights into Brand Image Using Online Consumer-Generated Product Reviews," *International Journal of Electronic Commerce* (20:1), Fall, pp 112-141.

Germann, F., Lilien, G.L. and Rangaswamy, A. 2013. "Performance implications of deploying marketing analytics," *International Journal of Research in Marketing* (30), pp 114–128.

Germann, F., Lilien, G.L., Fiedler, L. and Kraus, M. 2014. "Do Retailers Benefit From Deploying Customer Analytics?," *Journal of Retailing* (90:4), pp 587-593.

Kaptein, M. and Parvinen, P. 2015. "Advancing E-Commerce Personalization: Process Framework and Case Study," *International Journal of Electronic Commerce* (19:3), Spring, pp 7-33.

McAfee, A. and Brynjolfsson, E. 2012. "Big Data: The Management Revolution," *Harvard Business Review*, October 2012, pp 60-68.

Official Statistics of Finland 2015. "Use of information and communications technology by individuals." http://www.stat.fi/til/sutivi/2015/sutivi_2015_2015-11-26_tie_001_en.html Retrieved 29 March, 2016.

Piotrowicz, W. and Cuthbertson, R., 2014. "Introduction to the Special Issue: Information Technology in Retail: Toward Omnichannel Retailing," *International Journal of Electronic Commerce* (18:4), Summer, pp 5-16.

Pousttchi, K., Tilson, D., Lyytinen, K. and Hufenbach, Y. 2015. "Introduction to the Special Issue on Mobile Commerce: Mobile Commerce Research Yesterday, Today, Tomorrow–What Remains to Be Done?," *International Journal of Electronic Commerce* (19:4), Summer, pp 1-20.

TNS Gallup 2015. https://www.tns-gallup.fi/mita-teemme/digitaaliset-tutkimukset Retrieved 15 May, 2015.

Verkkoteollisuus 2015. "Selvitys: suomalainen verkkokauppias myy suomeksi suomalaisille." http://www.verkkoteollisuus.fi/toiminta/selvitys-suomalainen-verkkokauppias-myy-suomeksi-suomalaisille Retrieved 29 March, 2016.