University of Economics, Prague

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INTEGRATION OF VOICE OF CUSTOMER INTO CUSTOMER EXPERIENCE MEASUREMENT

Doctoral Dissertation

by

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Study program: Applied Informatics

Prague, Czech Republic

November 2019

A thesis submitted to the Department of Information Technology in conformity with the requirements for the degree of Doctor of Philosophy.

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When citing please use the following reference:

Šperková, L.: Integration of Voice of Customer into Customer Experience Measurement (Doctoral dissertation). University of Economics, Prague, 2019

Statement of Originality

I hereby certify that all of the work described within this thesis is the original work of the author. Any published (or unpublished) ideas and techniques from the work of others are fully acknowledged in accordance with the standard referencing practices.

Lucie Šperková

November 2019

Acknowledgements

Firstly, I would like to thank my supervisor doc. Ing. Ota Novotný, PhD. for his patient guidance during the writing of this thesis and continuous support and motivation of all of my studies and related research.

I am also grateful to George Feuerlicht who supervised me during my time as a visiting student at the University of Technology in Sydney, and Berry Jay who was tutoring me in the Technical Research Methods class which helped me to structure the Introduction chapter.

Next, my sincere thanks belong to my colleagues and co-authors from the faculty, namely Tomáš Bruckner, Filip Vencovský and Pavel Jašek for inspiring discussions, motivation and feedback. To Zdeněk Smutný and Lenka Vraná for their expertise in statistics and research methods, and all the other colleagues from the faculty who supported me and provided feedback on the thesis.

I would also like to thank Martin Fridrich from the Technical University of Brno whose expertise in statistics and programming enriched the performance of text analytics methods, and Jan Tyl for the opportunity to use the deep learning for emotion recognition.

Many thanks also belong to non-disclosed participants of the qualitative research, who offered me their time for interviews; to stakeholders of the researched company for access to the real-world dataset and implementation evaluation. To all experts for their opinions on practical managerial benefits of the research during the artefact validation.

Valuable comments and suggestions were also provided by reviewers of all my published journal articles which are an essential part of the thesis.

Finally, I am endlessly grateful to my parents who economically supported me during the whole time of my studies, and all the friends who believed that I would reach the last step of this long journey.

Abstract

The dissertation focuses on consolidated Customer Experience Measurement based on the integration of information mined from customer data in a textual form known as Voice of Customer (VoC). The main objective of this thesis is the creation of an artefact in the form of the Customer Experience multidimensional data model combining the information from textual VoC with other structured customer data extracted from various sources. The artefact enhances the currently fragmented methods in Customer Experience Measurement by providing more sophisticated data-driven and methodological approaches. In particular, text analytics is not yet fully established in marketing. The data model is divided into the textual and analytical part. Text analytics methods are performed during ETL processes. Following the Business Intelligence principles, different metrics are designed to track overall Customer Experience from the customer's perspective at each stage of the customer journey.

Based on literature research, the author conceptualises the Customer Experience construct and defines its constituent elements. Customer Experience Measurement is further enhanced with detection of sentiment, emotions and personality traits – perceptual elements hidden in customers' written expressions which emerge in their behaviour and accompany the entire customer journey. The author defines requirements on mining these elements with an emphasis on maintaining a customer perspective.

The qualitative research among Czech organisations operating in the internet environment shows the immaturity in Customer Experience Measurement and lack of approaches to mine the information from textual VoC. The artefact is validated by Technical Action Research (TAR) in an e-commerce environment with real-world datasets. The author analysed textual customer data in the form of customer reviews with a set of text analytics methods – a lexicon-based approach for customer sentiment, rule-based approach and Latent Dirichlet Allocation for aspects detection, deep-learning for emotions mining, and clustering for personality detection. The results of methods met the stated criteria and were integrated with other structured data within Customer Experience data model. The proposed reports, which maintain the customer perspective, have successfully met the stakeholders' goals. Beside TAR, seven expert opinions validated the usability of the artefact and assessed its managerial impacts. Experts agreed that the artefact mitigates the barriers of achieving the full potential of analysing VoC within Customer Experience mentioned in Czech companies. The artefact is thus properly designed and ready to be utilised by business practitioners.

Keywords: Voice of Customer, Customer Experience, data model, text analytics, sentiment analysis, aspect detection, emotions, personality traits, customer satisfaction, measurement, management

Abstract in Czech / Abstrakt

Disertační práce se zaměřuje na konsolidované měření zákaznické zkušenosti (Customer Experience), založené na dolování informací ze zákaznických dat v textové podobě (Voice of Customer). Hlavním cílem práce je vytvoření artefaktu v podobě multidimenzionálního datového modelu. V něm jsou kombinovány informace z textů zákazníků s dalšími strukturovanými zákaznickými daty pocházejících z různých zdrojů. Artefakt obohacuje současné roztříštěné metody v měření zákaznické zkušenosti o sofistikovanější, datově řízené a metodologické přístupy. Využívá především domény textové analytiky, která v marketingu zatím není zcela etablována. Datový model je rozdělen na textovou a analytickou část. Metody textové analytiky jsou prováděny během procesu extrahování, transformace a nahrávání do databáze. V rámci artefaktu jsou navrženy metriky ke sledování celkové zákaznické zkušenosti z pohledu zákazníka v každé fázi zákaznické cesty.

Na základě rešerše autor konceptualizuje konstrukt zákaznické zkušenosti a určuje jeho základní prvky. Dále obohacuje měření zákaznické zkušenosti o detekci sentimentu, emocí a osobnostních charakteristik – percepčních prvků skrytých v písemném vyjadřování zákazníka. Tyto prvky odrážejí chování zákazníka a provázejí celou zákaznickou cestu. Autorka definuje požadavky na dolování těchto prvků z textu s důrazem na zachování zákaznické perspektivy.

Kvalitativní výzkum mezi českými společnostmi operujícími v prostředí internetu ukazuje nevyspělost v měření zákaznické zkušenosti a v dolování informací ze zákaznických textů. Artefakt byl zvalidován metodou technického akčního výzkumu (TAR) na reálných datech z prostředí e-commerce. Autorka zanalyzovala textová data v podobě zákaznických recenzí sadou metod textové analytiky – využila slovníkového přístupu k určování sentimentu, přístupu založeného na pravidlech k detekci aspektu, latentní dirichletové alokace pro určení kategorií aspektů, hlubokého učení pro určení emocí a shlukování pro detekci osobnosti. Výsledky metod, které splnily definovaná kritéria na dolování prvků, poté autorka zintegrovala s dalšími strukturovanými daty z jiných zdrojů do modelu zákaznické zkušenosti. Navržený reporting s měřením, který zachovává zákaznickou perspektivu, úspěšně naplnil cíle zúčastněných stran. Vedle TAR, sedm expertů prokázalo využitelnost artefaktu v praxi a zhodnotilo jeho manažerský dopad. Dle expertů artefakt zmírňuje bariéry využití plného potenciálu analýzy zákaznických dat v rámci měření zákaznické zkušenosti, definované během kvalitativního výzkumu. Artefakt je tedy vhodně navržen a připraven k použití v praxi.

Klíčová slova: Voice of Customer, Customer Experience, datový model, textová analytika, sentiment analýza, detekce aspektu, emoce, osobnost, zákaznická spokojenost, zákaznická zkušenost, měření, řízení

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[2] Unless otherwise stated, all tables are processed by the author.

List of Abbreviations

BI	Business Intelligence
CLV	Customer Lifetime Value
CRM	Customer Relationship Management
CRISP-DM	CRoss-Industry Standard Proces for Data Mining
CVM	Customer Value Management
CX	Customer Experience
EIS	Enterprise Information System
ERP	Enterprise Resource Planning
ETL	Extract Transform Load
eWoM	electronic Word of Mouth
EXQ	Customer Experience Quality
HMM	Hidden Markov Model
ICT	Information and Communication Technology
LDA	Latent Dirichlet Allocation
LSA	Latent Semantic Analysis
MaxEnt	Maximum Entropy
NB	Naïve Bayes
NLP	Natural Language Processing
NPS	Net Promoter Score
OLAP	Online Analytical Processing
PMI	Pointwise Mutual Information
PoS	Part of Speech
QFD	Quality Function Deployment
REST API	Representational State Transfer Application Programming Interface
RFM	Recency, Frequency, Monetary
ROI	Return of Investment
SVM	Support Vector Machine
TAR	Technical Action Research
VoC	Voice of Customer
WoM	Word of Mouth

Chapter 1

Introduction

Current marketing practices emphasise the customer in the Internet environment and focus on the creation and subsequent evaluation of the customers' and service users' interactions for a customer-centricity approach. **Customer Experience** is considered as a tool to improve the value of customer and company (Gentile, Spiller & Noci 2007) through observation and measurement of all the customers' cognitive and affective outcomes emerged from the customer's exposure or interaction with a company's people, processes, technologies, products, services and other outputs (Buttle & Maklan 2015) relating to their purchasing behaviour (Klaus 2015).

With the growth of e-commerce, the entire lifecycle of the customer has its online version. Current approaches store data about customers and marketing activities mainly in relational databases in Enterprise Information Systems (EIS) like CRM, ERP[3] or web analytics platforms. Consumers, however, increasingly share their opinions and behaviour with other consumers, and communicate with organisations across channels of various character including emails, calls, chats, and even activity on social networks or online forums.

This form of communication through different channels is called **Voice of Customer** and comes in the form of textual data which are unstructured and can be broken in several ways – by content, tone, sentiment, emotion or criticality. It involves opinions of the customer about the various products, services or issues of the company. When the communication is broken down and analysed, a new dimension of the customer arises. Text analytics enables to add a new, more profound level of granularity which subsequently enables the discovery and analysis of more actionable information. Extracting information from the textual content and breaking it into dimensions is an effective method to integrate such large amount of textual data into a customer analytical model, which will serve as a source of data for a comprehensive measurement of Customer Experience.

Research in Customer Experience is mainly based on surveys (e.g. Klaus 2015) or proposed conceptual models (e.g. Lemon & Verhoef 2016). The sources of data for Customer Experience Measurement is mainly manually collected data, data from social media or other external sources, and data stored in EIS such as analytical CRM. Due to the complexity of the

[3] Customer Relationship Management, Enterprise Resource Planning

Customer Experience construct, there is no uniform Customer Experience data model which could serve as a base for its measurement.

Customer Experience is closely related to and based on customers' perceptions, feelings, emotions and also personality traits. Companies are still struggling to understand and adopt customers' cognitive and emotional expressions during their customer journey. The author stresses the importance of the measurement of personality traits and emotions as they accompany the entire customer journey, thus the Customer Experience process. Both personality and emotions, together with the sentiment, are possible to detect from the textual Voice of Customer. Customer Experience model enhanced with such textual data enables companies to lead their marketing on an individual customer-oriented level, well-targeted across all sales channels during his journey. When analysing the feedback from customers for Customer Experience purposes, the company does not need to rely solely on the summary of the results of quantitative and qualitative research which is usually performed at the end of the customer journey. It can embrace its structured customer data with the information automatically gained from Voice of Customer with text analytics during the customer journey.

Monitoring of all customer activities and interactions with the company is broadly discussed in the literature[4]. Some efforts in the integration of textual data into business processes have been already made; however, companies predominantly approach textual data such as VoC separately, rather than in the integrated Customer Experience model. Additionally, research focuses more on analysing textual data from a product perspective (e.g. Yaakub 2015) rather than the customer dimension. There are still gaps in the integration of textual data into customer analytical models and between Voice of Customer Marketing and Customer Intelligence. Textual data such as those customer interactions exist in silos with limited use in Business Intelligence which is based on relational databases with data in a structured form. Usually, companies' approach is very fragmented, with the use of different tools within the multi-channel environment. This thesis is a case of a specific utilisation of Voice of Customer to Customer Experience using text analytics.

1.1 Applied Terminology

This thesis understands **Customer Experience** as a *"multidimensional construct focusing on a customer's cognitive, emotional, behavioural, sensorial, and social responses to a firm's offerings during the customer's entire purchase journey"*, according to Lemon and Verhoef

[4] In business practice, the integrated view of every customer is also know as 360 degree view of the customer.

(2016). This definition reflects and generalizes other researchers concluding that *"Customer Experience is the cognitive and affective outcome of the customer's exposure to, or interaction with, a company's people, processes, technologies, products, services and other outputs"* (Buttle & Maklan 2015) *"relating to their purchasing behaviour"* (Klaus 2015).

The notion **Voice of Customer** (VoC) has been adopted from the research of Griffin and Hauser (1993) where it was first used as a term for roofing customer needs in relation to quality. This notion was further expanded by the **Word of Mouth** (WoM) term in the same as Lemon and Verhoef (2016) or Schmidt- Subramanian (2014) understand it in their Customer Experience research. Anderson (1998) defines WoM as an informal communication carrying some emotion based on customer satisfaction with the product or service. The most recent definition was published in (Bronner & de Hoog 2010): *"Any statement – positive, negative or neutral – made by potential, current or former stakeholders about a product, service, company or person, which is made available to a multitude of people, organisations or institutions, via a digitally networked platform."* The author thus understands VoC as any content that a user has written or said, and considers its influence on other participants in this conversation as WoM. Based on the literature it can be concluded that the concept of Voice of the Customer is superior to the Word of Mouth concept, although the term WoM appears in literature much earlier before the existence of online marketing (Katz & Lazarsfeld 1955; Richins 1983) and often these concepts are understood as the same.

Text analytics is in this thesis understood according to (Reamy 2016) as an umbrella term for adding structure to unstructured/semi-structured text, turning text into data and looking for meaning and cognition through making that text more understandable and usable. Text analytics is the use of software and semantic structure resources to analyse text with different linguistic and computational techniques and the applications that are built using this analysis (Reamy 2016). Further terms regarding text analytics are continually explained in Chapter 4 and are based mainly on Bing Liu's monography "Sentiment Analysis" (Liu 2015).

1.2 Objectives

The following **objectives (O)** have been set for this thesis:

O1) To design the Customer Experience multidimensional data model enhanced with storing the information extracted from textual VoC.

The objective is to design a data model architecture for Customer Experience capable of storing information from textual VoC. The aim is to complete the internal data from Enterprise Information Systems like ERP, CRM or web analytics platforms with transformed information from textual data in a multidimensional database structured as fact and dimension tables. The model contains pre-defined tables for the results from the text analytics in a textual stage (detected opinions with their emotion or sentiment in textual VoC - see *O2* and *O3*) related to several dimensions enabling to access the data from the customer perspective. The linkage between tables with structured data must be found. The idea of this model is to combine the customer entity with other entities representing the customer perceptual and behavioural metrics of Customer Experience. All the customer data (transactional, demographical, behavioural and VoC data) are then stored in one consolidated physical location in a unified form. The objective of this thesis is not to bring the complex platform based on CRM, but an expandable and transferable data model containing the data from textual VoC among other data, which can be implemented in any Business Intelligence solution.

O2) *To enhance Customer Experience Measurement with new elements of customer sentiment, customer emotions and personality traits.*

The objective is to implement new elements serving as measures into Customer Experience, which is in this thesis understood as a construct of share-of-mind metrics. The emotion recognition, satisfaction detection and personality traits detection are based on textual VoC data. These detected elements are measured automatically with text analytics methods (see *O3*), and the data are contained in the Customer Experience data model. Elements enhance Customer Experience Measurement and its constituent metrics.

O3) *To validate the textual part of the Customer Experience model with the application of text analytics methods for extracting information from textual VoC.*

This objective aims to apply text analytics methods (sentiment analysis and aspect detection) based on current research to measure Customer Experience elements from textual VoC data and store the extracted information into the unified Customer Experience data model. The methods are performed during the ETL processes. The aim is also the validation of the textual part of the multidimensional data model designed in *O1*. The applied text analytics methods should gain acceptable results with adequate computing time. Objective enhances current Customer Experience approaches with data-driven analysing of VoC.

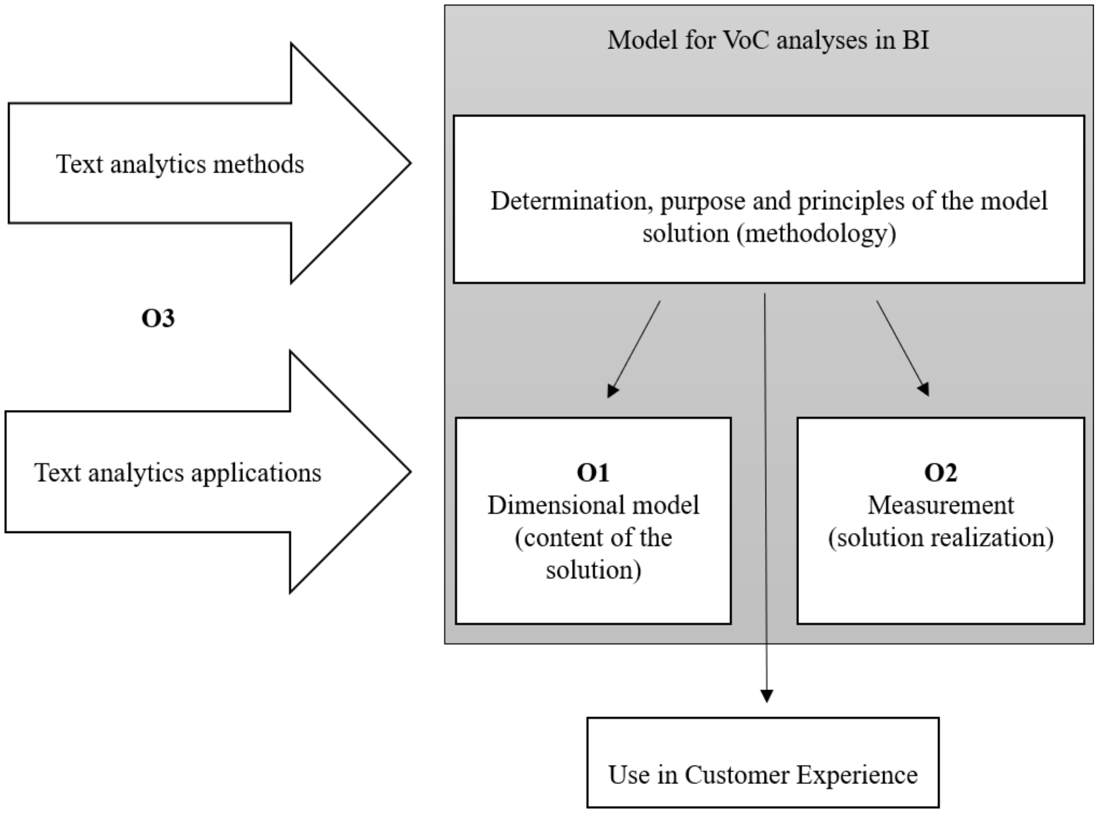

Figure 1.1: Reference model for Voice of Customer analysis using Business Intelligence tools

To meet the objectives, the author designed a reference model in Figure 1.1, which serves as a guide through the whole research process. Different parts of the model are linked to the objectives. The reference model follows the general approach to Business Intelligence (BI). Bringing textual VoC into the structured environment for useful analyses requires the textual data to be subjected to a rigorous process of integration and preconditioning (Inmon & Nesavich 2007). In this thesis, the Customer Experience data model is understood as a part of Customer Intelligence, which works on the basis of cleaned structured data, while customer interactions in the form of text are inherently unstructured data lacking formal organisation and coming from various sources. Unstructured data do not conform to a structured data model and cannot be queried nor processed directly by analytics systems (Ng et al. 2013). According to Inmon and Nesavich (2007), it is much easier to locate unstructured data in a structured environment rather than to reconstruct the analytical environment elsewhere. For purposes of analysis of the VoC content with BI, information obtained from VoC must be combined with information from existing structured data stored in a data warehouse.

A necessary condition for the solution is its simplicity and portability. A prerequisite is the use of existing methods and techniques for content and sentiment analyses of customers contributions within the analytical processes above the multidimensional database. One possibility is a connection of the relevant techniques in which case analysis will be carried out outside or within the core ETL processes, and the results will be saved to the database and combined with other structured data.

1.3 Research Questions

In compliance with design science methodology (Wieringa, 2014), the thesis proposes the following research questions based on defined objectives in section 1.1:

RQ1) What is the current situation in the use of Voice of Customer within the Customer Experience Measurement?

RQ2) How to incorporate Voice of Customer and its textual analytics into Customer Experience Measurement to further understand Customer Experience during the customer journey?

RQ3) What are the implications of an enhanced Customer Experience Measurement model to Customer Experience Management?

The relations between the objectives, research questions and deliverables discussed in the next section are depicted in Table 1.1 in section 1.8. The continuity between objectives and research questions supported by research methods are illustrated in Figure 1.3: Research methodology framework on page 20.

1.4 Research Methods

The research methodology employed in this dissertation is driven by the Design Science methodology (Vaishnavi & Kuechler 2015; Wieringa 2014) emphasising the discovery of new knowledge of a problem domain by the construction and application of designed artefact. Such artefacts should also be rigorously evaluated, and they should contribute to addressing relevant business problems. The process of this research according to Design Science methodology is depicted in Figure 1.2. The artefact is represented by deliverables *D1* and *D2* (see section 1.5): Customer Experience data model and Customer Experience metrics. The artefact is validated and evaluated by Technical Action Research (TAR) according to (Wieringa & Morali 2012; Wieringa 2014) and with a panel of experts (Wieringa 2014). TAR is an experimental use of the artefact in the real world; an approach to validate a new artefact under conditions of practice. TAR is a particular kind of an action case study using engineering cycles for needs of improvement through designing a treatment - an artefact interacting with a problem context. The case in this thesis is validated in an e-commerce environment as one with the most advanced customer analytical data.

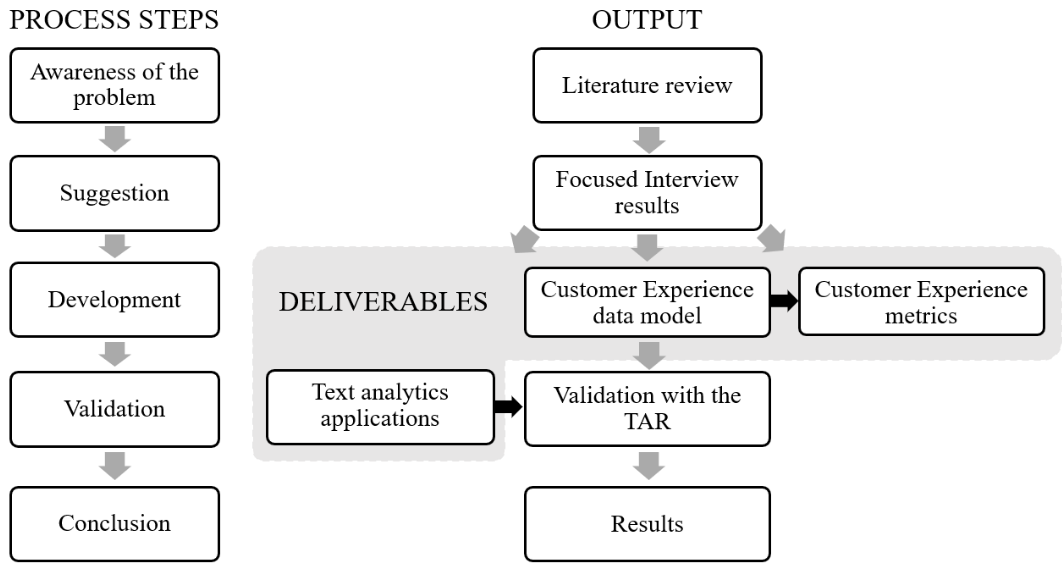

Figure 1.2: General methodology of design science research based on (Vaishnavi & Kuechler 2015)

Figure 1.3 conceptually introduces the framework for research methodology and explains the relationships between research questions, objectives and utilised research methods.

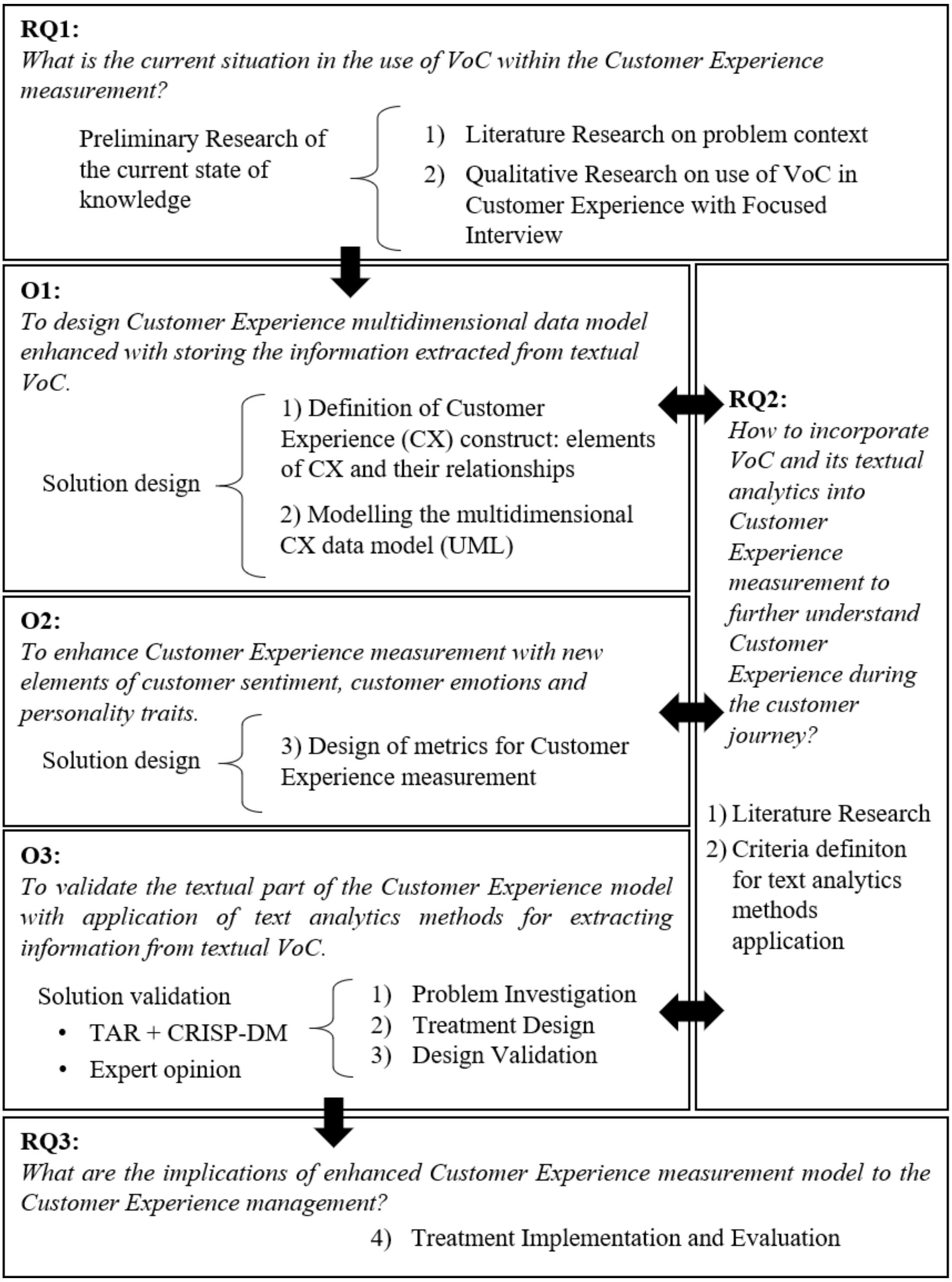

Figure 1.3: Research methodology framework

1.4.1 The Preliminary Research

The preliminary research aims to answer the *RQ1* and partially *RQ2*. The proposed steps are as follows:

1) **The literature research on problem context (search, critical analysis, interpretation and synthesis)** supports the knowledge in Customer Experience Measurement (Chapter 2) and text analytics in VoC (Chapter 4). It puts the current research in Customer Experience, Voice of Customer and Text Analytics in context – current measurement practices of VoC in marketing research, approaches used in Customer Experience Measurement and definition of the metrics, elements and their relationships within the Customer Experience, current state of VoC analyses by text analytics methods, research in emotion, satisfaction and personality traits, and their detection with text analytics.

2) **Qualitative Research by Focused Interviews** (Merton 2008) with representatives of Czech organisations operating in the B2C relationships within the Internet environment aims to evaluate the use of VoC in Customer Experience Measurement and management in organisations. The methodology of gathering data is in accordance with Yin (2009), Molnár et al. (2012), Myers (2013). The results of the research are also published in the author's article (Šperková 2019).

1.4.2 Solution Design

This part aims to fulfil the objectives *O1* and *O2*, which also bring the deliverables *D1* and *D2* (see section 1.5) as an artefact according to Design Science Research. Proposed steps are as follows:

1) **Definition of Customer Experience construct** is based on literature research results and puts existing constructs and metrics into mutual relationships in one conceptual model.

2) **Design of multidimensional Customer Experience data model** enhanced with storing the information extracted from textual VoC builds on the knowledge of the founder of data warehousing, Bill Inmon (Inmon 2002). The model respects the principles of multidimensional modelling, and the author uses the Unified Modelling Language (UML) class-based approach. The essential part of the model is formal naming and definition of the types, properties, and relationships of the entities that exist for a particular VoC domain. This thesis shows the logical data model.

3) **Design of metrics for Customer Experience Measurement** is based on customer sentiment, customer emotions and personality traits extracted from textual VoC by text analytics methods. Criteria for application of text analytics methods to gain the necessary elements and specification of metrics and their reporting are defined. The metrics are expressed from the BI perspective according to Kimball et al. (2015) based on dimensional modelling as indicators and their characteristics, analytical dimensions and their characteristics, and the relationship between dimensions and indicators. In this thesis, the metric is understood as a quantitative or qualitative indicator or an evaluation criterion to assess the level of Customer Experience with its constituent elements.

1.4.3 Validation of the Solution

The designed solution as an artefact is validated according to Design Science Research for information systems and software engineering (Wieringa 2014). Two methods of validation are performed: 1) validation with Technical Action Research (TAR) and 2) validation with expert opinions.

1) Validation with TAR

The designed artefact is implemented in a real-world case in Chapter 6, according to Wieringa & Morali (2012) and Wieringa (2014), who transferred the TAR to information systems design science. The process of implementation of text analytics methods into Customer Experience is inspired by CRISP-DM[5] (Chapman et al. 2000) adjusted to the textual data environment of VoC data according to the author's article (Šperková & Feuerlicht 2017).

I. **Problem investigation** defines the unit of the study and the specific problem in the real-world case, specifies the goals for stakeholders and justifies the value of the treatment.

II. **Treatment Design** represents a demonstration of the artefact interacting with a problem context. This phase contains data definition, selection of data sources, extraction, transformation and load (ETL) of relevant data to the multidimensional database. As a part of ETL, the implementation of chosen text analytics methods (as an objective *O3* which brings deliverable *D3*) is performed for determination and measuring Customer Experience elements from VoC textual data.

[5] CRoss-Industry Standard Proces for Data Mining.

III. **Design Validation** is based on observation and measuring how well the designed treatment supports a solution to the problem by comparing the objectives of the solution to actual observed results from the use of the artefact in the demonstration. The validation of the results gained by text analytics methods is based on statistical measures used in text analytics.

IV. **Treatment Implementation and Evaluation** aim to implement the designed treatment in a client company, evaluate the achievement of stakeholders' goals and discuss managerial implications of the results. Evaluation of the impact of metrics on Customer Experience Management partially answers *RQ3*.

2) Validation with Expert Opinion

In Chapter 7, the solution is submitted to a panel of experts to gain their insights and complete the validation of the artefact in a real-world context which varies among companies. Experts imagine how such an artefact will interact with problem contexts visualised in their minds and then predict the possible effects (Wieringa 2014, p. 63). The opinions are important feedback about the artefact as they can help with the improvement of the artefact and finding the mechanisms that they think will produce the effects.

1.5 Deliverables

The thesis brings the following deliverables:

D1) Multidimensional Customer Experience data model

The multidimensional data model extends the structured relational data from Enterprise Information Systems commonly used as underlying data for Customer Experience Measurement for the information gained from the unstructured textual data in dimension and fact tables. Data essential for the determination of Customer Experience elements of satisfaction, emotions and personality traits are stored in the model combined with the data for determining the typical perceptual and behavioural measures. The model contains its textual and analytical stage. Together the data can be further analysed through analytical techniques with the analysing of patterns in customer data and used to streamline Customer Experience Management.

D1a) Customer Experience construct as an enhanced conceptual model

A conceptual model represents known elements of Customer Experience and their relationships during the customer purchase journey. The model includes elements of personality and emotions which were not modelled in the context in any Customer Experience conceptual model in current research. The construct captures an iterative and dynamic character of Customer Experience during the customer journey.

D2) Set of metrics evaluating Customer Experience from the customer's perspective based on elements of sentiment, emotions and personality traits.

The deliverable brings new elements integrated into Customer Experience Measurement – personality traits, emotions and satisfaction perceptions with the sentiment. The metrics are based on the Customer Experience construct designed as a deliverable *D1a*. The underlying data for new elements of Customer Experience are determined with the application of text analytics methods from textual VoC data (*D3*), added to the data model and subsequently reported in comprehensive Customer Experience Measurement.

D3) Application of text analytics methods suitable for determining and measuring Customer Experience elements based on VoC textual data

Sentiment analysis and aspect detection methods are chosen based on the literature research, available data and stakeholders' problems in the case study. Their suitability is critically discussed in relation to the problem the methods solve and the environment where the methods are performed. The limitation of this environment is the language – the author performs an analysis of the textual data in the Czech language. The methods are applied in practice on real-world VoC datasets.

Table 1.1 in section 1.8 shows the structure of the research and the mapping between objectives, deliverables, research questions and research methods in chapters.

1.6 Significance

This dissertation has an interdisciplinary character and demonstrates the benefits of informatics in marketing research. It links the three areas of research (see Figure 1.4): Voice of Customer, Customer Experience and Text Analytics. Critical reflection on the current understanding of Customer Experience and VoC in marketing research brings to light a missing integration of knowledge from earlier studies. Review of text analytics methods, mainly for the detection and analysis of elements of sentiment, emotions and personality, is incorporated to complement the knowledge and to extend the possibilities of measurement of the Customer Experience with data-driven analytics of textual VoC. Academic and scientific benefits consist of the transfer and synthesis of existing theoretical concepts into a Customer Experience construct. The thesis focuses on Customer Experience from a customer perspective rather than an established company perspective based on aggregated customer data or product perspective typical for sentiment analysis. The inclusion of sentiment, emotions and personality traits detected by information technology, which is not yet entirely entrenched, brings new essential elements to evaluate Customer Experience. The focus on textual data in the Czech language enriches the research in Czech for application of the methods in business practice.

The designed data model for inclusion textual VoC and the following measures which are part of Customer Experience construct should significantly streamline marketing efforts during the customer journey. The thesis is a case of specific utilisation of VoC in Customer Experience as a part of the marketing strategy rather than creating a separate strategy only for textual data.

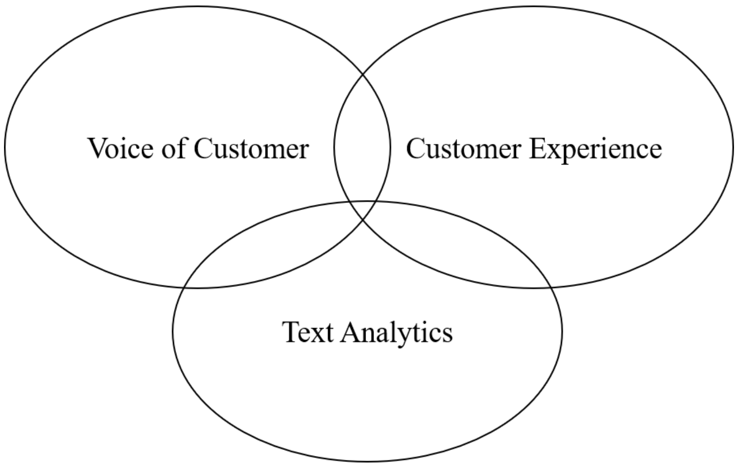

Figure 1.4: Interconnection of the three areas of the research

The stakeholders of this thesis are all customer-facing employees. The author expects a positive impact on Customer Experience Management based on the results from designed metrics which help to manage an improved experience of the customer during their journey. These results are shared through the company in consolidated reports, so all the stakeholders have identical insights that can move to the level of an individual customer. The actions based on these results increase the performance of the organisation and improve decision making, from which benefit mainly employees in managerial positions. Other stakeholders are data and marketing analysts who work directly with customer data. The designed Customer Experience data model and the following metrics simplify comprehension of Customer Experience construct. Selected text analytics methods are instructions on how to solve virtually VoC data within Customer Experience Management.

The work is based on rigorous elements from various academic disciplines, including Business Intelligence, marketing, information retrieval and system designs. Due to the retrieval of customer emotions and personality traits from VoC data, the thesis overlaps with cognitive science, neuroscience and psychology, which enhance data-driven text analytics methods. The dissertation contributes to the application and use of new methods in Customer Experience. It shows the importance of using both structured and unstructured data for Customer Experience Measurement for generating more in-depth insight, instead of using either one individually. It also shows the importance and utilisation of text analytics in Customer Experience. The perceptual and behavioural customer metrics – such as loyalty or satisfaction – are automatically determined from user-generated content as underlying data for these metrics. Detection of information from the textual VoC with text analytics reduces manual identification of customer needs. Organisations can thus develop effective business strategies related to marketing, customer support, and product design functions in a timely fashion. In contrast to the reviewed work, the thesis bridges the gap between computer science and marketing and represents an example of a specific application of text analytics into Customer Experience.

1.7 Publications

This thesis follows more than five years of the author's research and business practice. The author participated as a researcher in two projects financed by the Internal Grant Agency (IGA) which are thematically very close to the thesis: In 2014 and 2015 a grant project "Innovative View to the Customer and Other Factors Affecting Marketing Management" (F4/18/2014) and in 2015 and 2016 a project "Innovation Evaluation of the Quality of ICT Services Through the Analysis of Unstructured Data". The 2018 – 2021 project financed by Technology Agency of the Czech Republic (TACR) "The Customer Lifetime Value in the Environment of Cultural Institutions" is currently running under the aegis of Department of Marketing of Faculty of Business Administration at the University of Economics, Prague. As part of these ongoing grant projects, the author published outputs which were included under these grants and are also the partial results of this dissertation. Selected parts of this thesis have been developed in support of these grants. The lists in which the article is indexed are indicated in brackets after each relevant entry.

1.7.1 Journal Papers

Šperková, L. (2019). Qualitative Research on Use of Voice of Customer in Czech Organisations. *Journal of Systems Integration*, *10*(2), pp. 9-18.

Jašek, P., Vraná, L., Šperková, L., Smutný, Z., & Kobulský, M. (2019). Comparative analysis of selected probabilistic customer lifetime value models in online shopping. *Journal of Business Economics and Management*, *20*(3), pp. 398-423. ***(Web of Science - JCR, Scopus, 2018 IF: 1.855, 2018 SJR: 0.389)***

Jašek, P., Vraná, L., Šperková, L., Smutný, Z., & Kobulský, M. (2019). Predictive Performance of Customer Lifetime Value Models in E-Commerce and the Use of Non-Financial Data. *Prague Economic Papers,* 28(1), pp. 1-22. ***(Web of Science - JCR, Scopus, 2018 IF: 0.629, 2018 SJR: 0.287)***

Šperková, L., 2018. Review of Latent Dirichlet Allocation Methods Usable in Voice of Customer Analysis. *Acta Informatica Pragensia*, *7*(2), pp.152-165. ***(ERIH, RVVI list)***

Jašek, P., Vraná, L., Šperková, L., Smutný, Z., & Kobulský, M. (2018, March). Modeling and application of customer lifetime value in online retail. In *Informatics* (Vol. 5, No. 1, p. 2). Multidisciplinary Digital Publishing Institute. ***(Scopus, ESCI)***

Šperková, L.,& Feuerlicht, G. (2017). Application of CRISP-DM to Voice of Customer and BI integration, In *Progress in Intelligent Computing and Applications (PICA), 5*(1), pp. 7–13.

Šperková, L., Škola, P., & Bruckner, T. (2015). Evaluation of e-Word-of-Mouth through Business Intelligence processes in banking domain. *Journal of Intelligence Studies in Business*, *5*(2)., pp. 36-47. ***(Scopus, ERIH, ESCI, 2018 SJR: 0.282)***

Šperková, L., Vencovský, F., & Bruckner, T. (2015). How to Measure Quality of Service Using Unstructured Data Analysis: A General Method Design. *Journal of systems integration*, *6*(4), pp. 3–16.

Šperková, L. (2014). Analýza nestrukturovaných dat z bankovních stránek na sociální síti Facebook. *Acta Informatica Pragensia*, *3*(2), 154-167. ***(RVVI list)***

1.7.2 Conference Papers

Vencovský, F., Bruckner, T., & Šperková, L. (2016, July). Customer Feedback Analysis: Case of E-banking Service. In *3rd European Conference on Social M di R h Media Research EM Normandie, Caen, France* (p. 404). ***(Web of Science - CPCI)***

Šperková, L. (2016). Využití analýz obsahu Voice of Customer v marketingu. In: *Sborník prací účastníků vědeckého semináře doktorského studia FIS VŠE v Praze*, Praha, pp. 42-52.

Šperková, L., & Škola, P. (2015). Design of Metrics for e-Word-of-Mouth Evaluation From Unstructured Data for Banking Sector. In: *16th European Conference on Knowledge Management*, Udine, pp. 717-725. Academic Conferences International Limited. ***(Web of Science - CPCI, Scopus – CP, 2018 SJR: 0.134)***

Vencovský, F., & Šperková, L. (2015). IT Service Quality Model: Evaluation of Quality In Use. In: *16th European Conference on Knowledge Management*. Udine, pp. 821-827. Academic Conferences International Limited. ***(Web of Science - CPCI, Scopus – CP, 2018 SJR: 0.134)***

Šperková, L., & Škola, P. (2015). E-WoM Integration to the Decision-Making Process in Bank Based on Business Intelligence. *Proceedings of the 23nd Interdisciplinary Information Management Talks*, pp. 207-216. Springer. ***(Web of Science - CPCI, Scopus – CP, 2018 SJR: 0.109)***

Šperková, L. (2014). Word of Mouth analysis on facebook in banking. In: *Marketing identity*. Smolenice, pp. 236-252. Trnava: Univerzita sv. Cyrila a Metoda v Trnava. ***(Web of Science - CPCI)***

1.8 Limits of the Dissertation

As the area of the research topic is extensive, the defined objectives limit the scope of the dissertation to the extent that assures solution of the problematics at a reasonable level of complexity and verification of fundamental ideas and principles. The too-broad area of the application of the artefact would make its design difficult. Thus, the focus of the research is limited to the business-to-consumer (B2C) setting operating in an internet environment. The correct functionality of the proposed artefact is aimed in small to medium-sized companies and is validated with expert opinion. The treatment is limited to only one part of the artefact verified by the specific goals of the stakeholders in the company where treatment is designed with the available data according to TAR. In broader context would be necessary to consider the new possibilities that may arise with an increasing number of areas of deployment and different conditions (for example, new sources of data or different text analytics methods).

In Customer Experience, the focus is on its measurement from a customer perspective, which can be supported by data analysis. That means the focus is on individual customer-level data. The source of data is textual expressions of customers combined with structured data gained from different EIS. Other sources, such as facial expressions or tone and rhythm of the voice in a speech, which also could influence Customer Experience, are not solved in this thesis. The scope of data is limited to the fundamental basis to build the model and the following metrics, as there exist many sources of potential customer data according to fast development in the area of new platforms and tools. The author generalises concepts to include any source which can extend the model and metrics if necessary.

The implementation of text analytics methods is narrowed down to the Czech language as the research is performed within the environment of Czech companies and with the data in the Czech language. The Customer Experience data model represents the results of text analytics methods, not the individual steps with intermediate results. The purpose of the reporting in Customer Experience is not an analysis of social media networks, rather an analysis of the current customer base of the company.

The last limitation is a validation of the detection of personality traits. Due to the General Data Protection Regulation[6] that came into force during the writing of this thesis in 2018 and the Cambridge Analytica scandal with Facebook (Isaak & Hanna 2018), the author cannot experiment with the personality questionnaire provided to customers to validate the results gained from their textual feedback.

1.9 Structure of the Dissertation

The Introduction chapter stated the objectives, significance, research questions and research methods on which this thesis is constructed. The rest of the structure of the dissertation is outlined in Table 1.1.

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[6] General Data Protection Regulation. More information at https://eur-lex.europa.eu/content/news/general-data-protection-regulation-GDPR-applies-from-25-May-2018.html

Table 1.1: The structure of the dissertation

Chapter	Objective	RQ	Deliverable	Research Method
Chapter 2	-	RQ1	D1a	The literature search, critical analysis and interpretation
Chapter 3	-	RQ1	-	Qualitative research with focused interviews
Chapter 4	O3	RQ2	D3	The literature search, critical analysis and interpretation
Chapter 5	O1	RQ2	D1	Design of the multidimensional CX data model represented by the UML class schema diagram
	O2	-	D2	Design and definition of CX metrics
Chapter 6	O3	RQ2 RQ3	D3	Validation of the artefact (deliverables) with the TAR method Application of text analytics methods following the CRISP-DM methodology
Chapter 7	-	-	-	Validation of the artefact (deliverables) with the expert opinions
Chapter 8	O1 – O3	RQ1 – RQ3	D1 – D3	Discussion

Chapter 2 is a theoretical introduction to Customer Experience and a critical analysis of the current state of approaches used in Customer Experience and its measurement. The chapter explains the role of VoC in customer analytics and marketing and emphasises the importance of VoC data in the measurement of Customer Experience. The chapter analyses contemporary marketing approaches, methods and practical use of VoC. Next, the chapter analyses the impact of emotions, satisfaction and personality traits on Customer Experience. Additionally, the chapter discusses the need for a Customer Experience data model. Designed Customer Experience construct is a conceptual model which puts in context all the currently measured metrics which are in research performed outside or inside the Customer Experience.

In Chapter 3, the results of the qualitative research conducted with focused interviews are discussed. The aim of the interviews is Czech organisations operating in the B2C relationships within the Internet environment. The goal is to assess the situation of measurement and management of Customer Experience with the support of VoC data in these companies. This chapter was published in the author's article in the Journal of System Integration (Šperková 2019).

Chapter 4 provides the introduction to text analytics of VoC with the focus on opinion mining and aspect detection techniques, which are further used in the treatment design in Chapter 6. Next, the chapter discussed the requirements for the text analytics methods which need to be performed for the mining the elements of Customer Experience. As the treatment design is based on Czech textual data, the research in sentiment analysis in the Czech language is also discussed. The chapter also describes the progress in the research of emotion mining and personality traits detection from textual data. In the last sections, the chapter focuses on methods in the integration of VoC to Business Intelligence and CRISP-DM methodology as a framework for text analytics processes. The chapter also mentions the author's previous work.

The multidimensional data model for Customer Experience enhanced with storing the textual data results from Voice of Customer is designed in Chapter 5 besides its measurement. The model is designed to fulfil the data requirements on calculations and determinations of Customer Experience metrics designed and explained according to the Customer Experience construct. The chapter explains the architectural framework of the solution, describes the textual and analytical part of the model and proposed metrics. In the end, the benefits of the artefact are discussed.

Chapter 6 validates the textual part of the artefact with the Technical Action Research. The treatment in the real-world case in an e-commerce company evaluates the artefact's usefulness. The treatment involves the mining and integration of customer sentiment, emotions and personality with their opinion targets to the Customer Experience data model from Chapter 5 by applying the text analytics methods based on stakeholders' criteria. The application of the text analytics methods follows the CRISP-DM methodology. The treatment design and its implementation to the stakeholders' environment are evaluated by fulfilling their goals. Implications of the treatment to Customer Experience Management are discussed at the end of this chapter.

In Chapter 7, the artefact is presented to a panel of experts assessing its applicability and validity. Chapter 8 discusses the findings of the dissertation. The research questions are answered, and the fulfilment of the objectives is evaluated. In the end, the chapter proposes further research recommendations. Chapter 9 concludes the thesis.

Chapter 2

Customer Experience Measurement

Creating a Customer Experience is currently a leading management objective, and its measurement plays a critical role in making insights actionable for the company (Lemon & Verhoef 2016). Increasing focus on Customer Experience emerges with more complex customer journeys resulting from multiple touchpoints and channels the customers interact with companies. Customer Experience is one of the most important research challenges in the coming years (Marketing Science Institute 2014, 2016).

This chapter advocates the inclusion of the thesis in the marketing field and customer analytics. Next, the chapter explains the construct of Customer Experience and puts it in relation to perceptual and behavioural customer metrics[7] in Figure 2.3 as deliverable *D1a*. Farris et al. (2006) classify these metrics as share-of-mind metrics, and in marketing research practice, these are known as customer feedback metrics (Morgan & Rego 2006). The chapter serves as a thorough analysis of these metrics within the Customer Experience concept. The chapter was created in the second half of the year 2016 and early 2017 with minor editing in 2019.

Research in Customer Experience is highly connected with previous research in customer satisfaction, service quality, customer relationship management, customer centricity, customer equity and customer engagement. Many conceptual models were designed (e.g. Parasuraman, Zeithaml & Berry 1988; Lemke, Clark & Wilson 2011; Gentile, Spiller & Noci 2007; Larivière 2008; Grewal, Levy & Kumar 2009; Klaus 2015; Lemon & Verhoef 2016) with different dimensions of research, for comparison see (Havíř 2017). The approaches to gathering data are based mainly on questionnaires and surveys (e.g. Larivière 2008; Brakus, Schmitt & Zarantonello 2009; Klaus & Maklan 2013; Klaus 2015; Khodadadi, Abdi & Khalili-Damghani 2016). The main focus of these studies and examined variables is summarised in (Khodadadi et al. 2016; Havíř 2017). Prior research has suggested that the customer's assessment of experience influences the share-of-mind metrics such as customer satisfaction, customer loyalty or Word of Mouth, but also customer profitability and Customer Lifetime Value (e.g., Bolton 1998; Bolton, Lemon & Verhoef 2004; Verhoef 2003).

[7] Which are measurable also with text analytics – see Chapter 4.

Individual metrics and their cause-effect relationships are well described in the marketing literature (Klaus 2015; Buttle & Maklan 2015; Hayes 2008). The detailed understanding of Customer Experience in the context of the customer journey and related marketing theories and measures offers the study of Lemon and Verhoef (2016). Author of this thesis understands Customer Experience as the roofing of all customer metrics discussed in this chapter, which is crucial to managing for better performance of all organisations. Also, Gupta and Zeithaml (2006, p.735) stress *"the need for more studies that view customer metrics comprehensively, rather than examining only a few constructs at a time".*

The chapter also sets the relationship between the Customer Experience and Voice of Customer (VoC) and reviews the current state of the research relating to VoC and its part Word of Mouth (WoM) from a marketing perspective. The chapter presents substantial concepts associated with the analysis of customer feedback and evaluation.

This thesis does not understand Customer Experience as a User Experience. Customer Experience is seen as superior to User Experience, which is considered as only one element of Customer Experience (see Figure 2.3) emerging during the use of the product or service, but not reaching the time prior or after the use. Customer Experience is going beyond the purchase and usage and encompasses prior expectation and post-evaluation, thus the entire customer journey.

This chapter, together with the results of the survey in Chapter 3, answers the research question *RQ1: What is the current situation in the use of Voice of Customer within the Customer Experience Measurement?* The chapter suggests incorporating VoC as an important source of data to enhance Customer Experience Measurement.

2.1 Thesis in the Concept of Marketing and Customer Analytics

Current marketing focuses on customer data and its monitoring and measurement. One of the basic principles of CRM is that it is much easier to sell into an established customer base than getting new customers. For years, research has shown that for the company it is roughly five to seven times easier and cheaper to continue satisfying existing customers than to try to gain new ones (Buchanan & Gilles 1990; Rud 2001). Reichheld and Teal (2001) stated that a 5% increase in customer retention would result in 35% to 95% increment in average Customer Lifetime Value. Gupta, Lehmann and Stuart (2004) found that 1% improvement in customer retention may increase firm value by about 5%. In this regard, creating a long-term relationship with the customer is indeed an essential requirement in today's holistic marketing (Karlíček et al. 2013, p. 18) bringing significant benefits to the firm (Storbacka & Lehtinen 2002).

Customer Experience is closely related to marketing research as a driver of customer acquisition and retention. Analysis, integration, and the use of customer textual data in Customer Experience relate to three dimensions of the holistic marketing according to (Kotler & Keller, 2013, p. 49 – see Figure 2.1) – relationship marketing, integrated marketing and performance marketing. VoC is necessary for marketing management at the company according to the performance of marketing activities and their metrics (performance marketing). The use of VoC involves the optimisation and streamlining of marketing campaigns and marketing research, which means cost optimisation, targeting and retargeting, customer-orientated approach and one-to-one marketing enhancing satisfaction and loyalty, and thus Customer Experience (relationship marketing), optimisation and automatization of the negotiation with the customer through different channels (integrated marketing). The customer is a central point of all marketing activities, not only because it generates income but also increases the market value of the company.

Figure 2.1: Dimensions of the holistic marketing concept. Source: (Kotler & Keller 2013, p. 49)

Customer analytics aims to improve business performance by enhancing customer satisfaction and driving up customer loyalty (Buttle & Maklan 2015) through the integrated view of every customer. Customer insight through analysing VoC allows companies to understand their customers better, predict their behaviour, and thus improve customer value propositions and experience to increase satisfaction. Today the trend is shifting towards Customer Experience, which encompasses all the perceptual and behavioural customer metrics in the same way the Customer Experience construct is understood in this thesis. In the customer-oriented market, the thorough knowledge of the customers and engagement with them represents an excellent prospect to be successful in the business with a sustainable competitive advantage in the market.

VoC provides feedback and valuable input about the Customer Experience for marketers who want to understand the behaviour of their customers. VoC is a rich source of customer data and their opinions, feelings and emotions. The goal of analysing VoC in textual form is to understand better what customers say, want or feel.

Voice of Customer appears in various forms of different sources as follows:

- In structured form as
    - the scales (ratings)
    - the results of structured questionnaires (customer surveys)
- In unstructured textual form as
    - direct feedback to the company (emails, calls, contact forms, websites chats, customer surveys)
    - the results of controlled studies (focus groups, narrative stories)
    - eWoM - the evaluation of Internet resources such as online forums, blogs, microblogs, social networks, customer reviews of products and services.

Interpretation of VoC can be divided typically into the automated and manual content analysis. The manual analysis is understood the case of human classification of text using a predetermined classification system without the aid of appropriate ICT tools mentioned in the context of advanced methods for the automated approach in Chapter 4.

2.2 Word of Mouth role in Customer Experience

The emergence of the new communication channels such as social media and the growth of popularity of e-commerce is a significant milestone for the Customer Experience Measurement giving rise to an important part of VoC – electronic version of Word of Mouth (eWoM) and new opportunities in VoC research. These channels simplify customer orientation and purchasing decision in a number and complexity of products and services of a similar quality which customers face. As customers can switch between companies at any time, Customer Experience is a critical instrument of relationship management. Consumers are considered active co-producers of value and importance as shows the Coproduction Network

Model (Figure 2.2) introduced in (Kozinets et al. 2010). The model displays the use of targeted one-to-one marketing, which intentionally and purposefully influences the customers and their opinions, and marketing messages and opinions spreading and exchanging among the members of the consumer network. Consumers are consequently influenced by the opinions of other consumers and can find information from various sources and make decisions regardless of what marketing offer claims. According to the research of BrightLocal (2016), 91% of consumers regularly or occasionally read online reviews, and 84% of people trust online reviews as much as a personal recommendation.

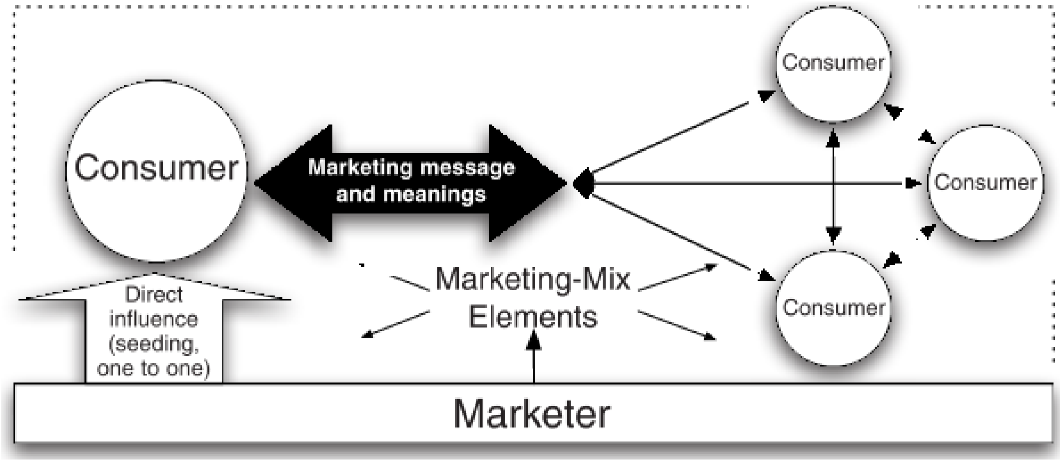


Figure 2.2: Network co-production model of WoM. Source: (Kozinets et al., 2010)

This sharing of customer behaviour through customer communication among themselves and companies on social networking applications of various character is known in the marketing field as Word of Mouth (WoM), in the Internet environment as electronic Word of Mouth (eWoM) (Choi & Scott 2013). The definition of WoM has been developed in time (Bone 1995, Anderson 1998, Helm & Schlei 1998, Hu, Pavlou & Zhang 2006, Hennig-Thurau et al. 2004, Bronner & de Hoog 2010, Huang et al. 2012). The evolution of the WoM definition and its mutual relation with the VoC concept and inconsistencies within the terminology is discussed in the author's article (Šperková 2016). The author of this thesis considers the best definition to be the combination of the definitions as published by Hu, Pavlou and Zhang (2006) and Bronner and de Hoog (2010): *"Any statement – positive, negative or neutral – made by potential, current or former stakeholders (customers) about an ownership, usage, or characteristics of particular product, service, company or person, which is made available to a multitude of people, organisations or institutions, via a digitally networked platform."* WoM is an inherently informal, non-certified, multilateral communication without any business purposes about a subject which may arise from both personal and impersonal sources. The effectiveness of these mainly external sources depends primarily on the factor of trust and experience. Some research considers WoM as the most potent promotion medium for the acquisition and retention of customers (Duhan et al. 1997; Winer 2009).

WoM, often as the primary source of information for customers, reflects the satisfaction and real customers' experience with the companies' products or services. Such WoM Helm and Schlei (1998) define as spontaneous WoM. An alternative to spontaneous WoM is organic WoM – recommendations of the brand or product by satisfied customers. Amplified WoM is the result of marketing activities that specifically support the rumours among the people (viral marketing). WoM has greater persuasiveness and contributes to increasing the credibility of and empathy for the product or service and their relevance to customers rather than marketer-generated content (Gruen, Osmonbekov & Czaplewski 2006; Bickart & Schindler 2001; Cheema & Kaikati 2010). As WoM can have an enormous impact on customer decisions, companies should be aware of its content as its understanding could be crucial in creating a successful marketing strategy.

The value of WoM is widely discussed in literature. Much of the marketing research explores the importance of the role and impact of WoM and its effects on **purchase decisions and sales** (Chatterjee 2001; Chevalier & Mayzlin 2006; Liu 2006; Park, Lee & Han 2007; Hu, Liu & Zhang 2008; Gupta & Harris 2008; Tsang & Prendergast 2009; Berger, Sorensen & Rasmussen 2010; Gu, Park & Konana 2012). Predicting the sales and purchasing decision based on review content and sentiment cover studies carried out by Godes and Mayzlin (2004), Dellarocas, Awad and Zhang (2007), Ghose, Ipeirotis and Li (2012) and Li, Wu and Mai (2019). Regarding Customer Experience elements there are studies evaluating WoM role and impacts on **customer behaviour and attitudes** (Bickart & Schindler 2001; De Bruyn & Lilien 2008; Park & Lee 2009; Godes & Mayzlin 2009); **customer loyalty** (Casaló, Flavián & Guinalíu 2008; Pang & Lee 2008; Gauri, Bhatnagar & Rao 2008; Gruen et al. 2006; Sun 2013); **service experience** (Pai et al. 2012; Vencovský, Bruckner & Šperková 2016); **service quality** (Qu, Zhang & Li 2008; Duan et al. 2013; Choudhury 2014; Song et al. 2016; Palese & Piccoli 2016; James, Calderon & Cook 2017; Vencovský 2018), **quality control** (Ashton, Evangelopoulos & Prybutok 2015), extracting **usability and user experience** (Hedegaard & Simonsen 2013), extracting **product features** and **consumers preferences** for the features (Lee & Bradlow 2011, Archak, Ghose & Ipeirotis 2011, Netzer et al. 2012). Finally, studies are researching **the impact of WoM in social networks** (Lü et al. 2011; Wu & Zheng 2012; Han & Niu 2012; Choi & Scott 2013; Groeger & Buttle 2014).

Earlier research focused solely on customer evaluation by quantitative metrics. The WoM and the ROI of marketing activities were typically measured with frequency of contributions and the number of people who receive them (e.g. Godes & Mayzlin 2004; Liu 2006), average rating value (Liu 2006; Wu & Zheng 2012), or in case of social networks the number of participants and quantitative estimation of the social influence. A common approach to WoM research is also experiments, simulations or surveys methods (Chan & Ngai 2011). The overview of major empirical studies in eWoM can be found in MIS Quarterly (Gao et al. 2015). Only a small number of studies within the WoM marketing applies text analytics (Berger et al. 2010; Robson et al. 2013; Zhang & Tran 2011; Dellarocas et al. 2007; Ghose, Ipeirotis & Li 2012). There are plenty of other studies examining the content of eWoM data, but with no relationship to the WoM marketing, but rather to text analytics discussed more in Chapter 4. These studies also tend to solve only specific problems and do not enhance the methods in the broader context of customer analytics.

The referral value of WoM is considered an important measure of success in business. It has a higher correlation with business performance than traditional measures like customer satisfaction (Reichheld 2003). However, customer satisfaction plays a leading role in spreading WoM. Satisfied customers transmit positive WoM, while disgruntled consumers produce negative WoM (Almossawi 2015). Negative information spreads faster than the positive kind (Chatterjee 2001; Sun 2013), and people tend to share more negative experiences than positive (Buttle & Maklan 2015). Negative comments have a higher power to persuade customers not to buy than positive comments and high ratings have the power to push to purchase decisions and profits generations (Chevalier & Mayzlin 2006; Robson et al. 2013). Improvement of Customer Experience may reduce negative WoM and gain engaged, satisfied customers spreading the positive WoM.

2.3 Expectation-Disconfirmation Construct

Most firms focus on a product/service-oriented quality rather than Customer Experience quality. Measurement of Customer Experience is commonly performed by the expectation-disconfirmation model of customer satisfaction, which is a comparison of customers' perception of experience with their expectations. Positive disconfirmation occurs when perception exceeds expectation. Negative disconfirmation occurs when the customer is dissatisfied. This model goes hand in hand with the theory of Zhang et al. (2016): in feedbacks, customers only mention features that did not meet or exceed their expectations.

Expectations are coming in the form of customer requirements or needs created by the pre-purchase experience. **Customer requirements** are those characteristics of the product or service that represent essential dimensions on which customers base their opinions about the product or service (Hayes 2008). These dimensions serve as quality dimensions for measuring service/product quality. **Customer need** is a customer's own words description, contained in VoC, of the benefit to be fulfilled by the product or service to achieve customer satisfaction (Griffin & Hauser, 1993). The concept of customer needs was already used in Quality Function Deployment (QFD) in manufacturing industries in the seventies. In QFD, customer needs are linked to designed attributes joining marketing issues and engineering issues. The quality is then the extent to which products meet the requirements of people who use them (Montgomery 2012). Griffin and Hauser (1993) are also the first who used VoC as a term for roofing customer needs. The goal of mining VoC is, according to Griffin and Hauser (1993), an understanding of customer needs and transforming them into critical functional requirements.

Expectation-disconfirmation theory expanded Parasuraman, Zeithaml and Berry (1985, 1988) in the SERVQUAL model related to service quality and identifying gaps between customer expectation and perception of the service during the value-of-use which need to be closed. Customer Experience was conceptualised as SERVQUAL plus (Lemke, Clark & Wilson 2011) in addition to the SERVQUAL model. SERVQUAL plus also considers a cognitive evaluation of expectations with emotional content and emotions, peer-to-peer interactions, usage of products and services by a customer, the relationship between supplier and buyer and brand communication and image. Service quality is important for the understanding of Customer Experience. The service quality issue solving by VoC analysis is discussed in detail in the author's articles (Šperková, Vencovský & Bruckner 2015; Vencovský & Šperková 2015).

WoM recommendations through product or service reviews directly influence customer expectations and subsequent rating after buying and after the product or service use. Huang et al. (2012) found out that WoM recommendations directly cause an increase in ex-post evaluation. The results of Duan et al. (2013) indicate that a better review ranking actually may lead to lower customer's review rating in the future due to high customer expectations. A customer with high expectations that were not met the expectations tends to write negative reviews which are significantly correlated with long reviews (Palese & Piccoli 2016). In this case, the customer expectation-disconfirmation gap leads to specific customer behaviour. Homogenous behaviour caused by the information overload (Zhang et al. 2016) and different cognitive processing (Hu, Pavlou & Zhang 2014) of customers with limited information-processing capacity can lead to similar customer's rating as is the cumulative average rating (Duan et al. 2013).

However, companies evaluate the customer reviews mostly with assigned structured numerical Likert-type scale ratings. Liu (2015) refers the rating scales to the sentiment polarity and intensity since online reviews reflect customers' opinions towards the products or services and express their sentimental attitude. Despite, this approach ignores the scope, content and context of WoM which has high credibility (Dellarocas et al. 2007; Tsang & Prendergast 2009) in the evaluation of the Customer Experience with the product or service. This type of evaluation lacks a precise definition of boundaries between the scale ratings (Robson et al. 2013) and specification what customers evaluate – product quality or their satisfaction with the product? Ratings from the product perspective are over-aggregated to capture customer's specific concerns and do not cover all subcategories that naturally appear in the review text (Qu, Zhang & Li 2008). Therefore, ratings can lead to misinterpretation and provide false information to reflect quality. The reviewer can give a full star rating, but at the same time, also write a comment evaluating the negative aspects of the product or vice versa. Different quality attributes collected from the text have a different contribution to an overall rating (Duan et al. 2013).

There has been proved statistically significant relationship (Qu, Zhang & Li 2008; Zhang et al. 2016) between the scales and comments which can be significantly affected by a variety of cognitive factors, such as extreme dissatisfaction and opinion heterogeneity (Zhang et al. 2016). Such ratings do not concentrate on the mean, instead, reflect the balance point of very different opinions. Their distribution is u-shaped (Hu, Pavlou & Zhang 2006), closely connected with the tendency to evaluate a product if customers feel a strong positive or negative emotion (Anderson 1998) according to the size of the expectation-disconfirmation gap. Thus, the reliability of quantitative measures based on online reviews in scales is questionable. Without a full understanding of WoM, it is impossible to evaluate its actual impact.

Many models measuring in some way Customer Experience from VoC use direct monitoring in the form of data survey questionnaires or interviews as a method of collecting data (Parasuraman, Zeithaml & Berry 1985; 1988; Cronin & Taylor 1992; Klaus 2015). They are easy to interpret since these programs focus on obtaining a score to measure the experience from periodical surveys with detailed multiple-scale items that correspond to experience dimensions which are evaluated with new surveys. The problem of those methods is the lack of flexibility and limitation to express customers' attitudes (Qu, Zhang & Li 2008) while they are tight with the dimensions, and missing spontaneity which can be gained from textual VoC. Evaluators only see what dimensions caused lower Customer Experience but can only presume the concrete reasons.

2.4 Customer Experience Construct

A considerable amount of previous research has examined the cause-effect relationship between customer satisfaction and service quality (e.g., Cronin, Brady & Hult 2000; Parasuraman, Zeithaml & Berry 1994). Customer Experience is context-specific and more complex than service quality and customer satisfaction. Customer satisfaction, service quality and WoM often measure only the intention, not the actual customer behaviour. Customer satisfaction is an overall assessment or attitude rather than an expectation-disconfirmation gap (Cronin & Taylor 1992) and should be considered as one of the components of Customer Experience, focusing on the customer's cognitive evaluation and fulfilment response of the whole experience or some part of it (Buttle & Maklan 2015). The Customer Experience Quality Model (EXQ) developed by Klaus (2015), stresses that customers also have pre-purchase or pre-direct encounter (past) experiences developed from another type of company's outputs such as advertising, promotion and WoM, including previous purchases, that lead to purchasing behaviour and experience after the purchase and consumption. Customer Experience is the entire process of searching, acquiring, integrating and deploying to achieve customers' aspirations encompassing every aspect of a company's offering.

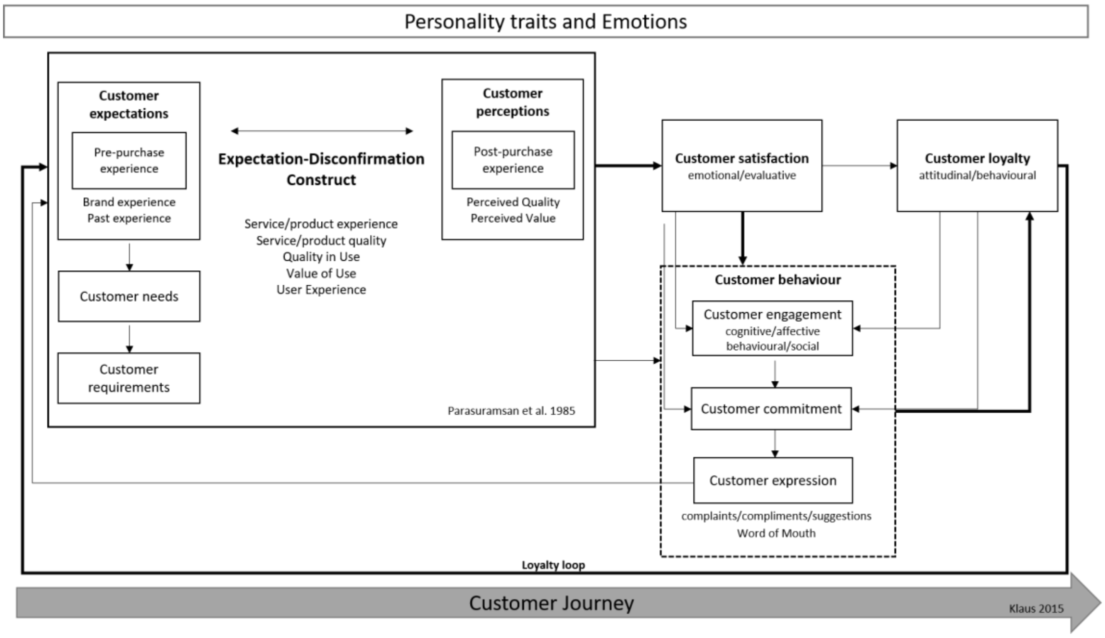


Figure 2.3: Customer Experience construct[8]

Customer Experience influences customers' perceptions of value and service quality, which influences their future behaviour and drives satisfaction which consequently affects

[8] The large picture of the figure can be found in Appendix B.

customer loyalty (Klaus & Maklan 2012; Lemke, Clark & Wilson 2011; Petre, Minocha & Roberts 2006; Schmitt 2010), but also WoM intentions (Keiningham et al. 2007). Customer Experience is the key driver for success and profitability in conformity with the satisfaction-profit chain (Buttle & Maklan 2015), a model designed by American Customer Satisfaction Index (ASCI) or service-profit chain framework in (Larivière 2008). Thus, Customer Experience can be considered as a part of the satisfaction-profit chain.

As shown in Figure 2.3, designed by the author, Customer Experience is an iterative and dynamic process flowing from the pre-purchase (including search) to the purchase and post-purchase stage with constant interactions of its constituent elements. This customer journey also includes loyalty loop (Court et al. 2009) which may be triggered in post-purchase stage and lead to either customer loyalty (through repurchase and further engagement) or begin a new process of re-entering the pre-purchase phase and consideration of alternatives.

Prior experience impacts current satisfaction, which in turn impacts future usage (Lemon & Verhoef 2016). Service quality and its constituent elements can be considered as an antecedent of Customer Experience. Also, engagement is considered a component of Customer Experience, mainly in the form of WoM through different touchpoints such as social networks or interactions with employees in the form of cognitive responses. The cognitive responses (De Keyser et al. 2015) are customer evaluations of what the company did (compliments), did not do (complaints), or could do differently (suggestions, requirements), affective responses show how customer feel during the experience (Shaver et al. 1987) with discrete emotions (see section 2.6.1). The cognitive and affective engagement reflects the experiences and feelings of customers, the behavioural and social engagement captures brand or organisational participation by consumers that goes beyond purchasing. Engaged customers are more committed to the company than customers who are just satisfied and exhibit higher attitudinal loyalty than unengaged customers (Hollebeek 2011). They are heavier referrers and more likely spread positive WoM and provide frequent feedback on their experiences (Buttle & Maklan 2015). Based on the degree of his commitment and level of loyalty, the strength of the relationship with the customer can be derived. According to (Haven & Vittal, 2008), the measurement of engagement is based on four indicators – intimacy, involvement, interaction and influence.

A good Customer Experience should build trust and loyalty. However, the loyalty can influence experience by reduction of cognitive effort and of attention paid to monitoring a relationship or through the halo effect (Lemon & Verhoef 2016). It is likely that newly acquired customers, freshly enthusiastic about their experience, would be powerful advocates of WoM, perhaps more than longer-term customers who are more habituated (East & Hammond 2000). Commitment is a measure of a customer’s connection with the company and can be understood as a succedent of Customer Experience. Together with loyalty, it can influence the customer’s subsequent experience and entry into the loyalty loop. This thesis considers engagement and commitment as a part of customer behaviour which emerges both from Customer Experience and the level of satisfaction and loyalty. Personality traits and emotions (described in section 2.6) are present during the whole process of Customer Experience and are latent to customer satisfaction and loyalty.

Customer Experience captures value-in-use of the organisations’ offering not just on price and the attributes of product or service (Klaus & Maklan 2012). It assesses, as much as possible, emotional responses as well as the functional delivery of the organisation’s promise. It determines the reasonable focal period, sufficiently before and after the service or product delivery, to allow the customer to assess the experience over time and across different channels (Klaus 2015). It is a multidimensional construct measuring during the entire purchase journey. The measurement of Customer Experience comprises a dynamic overall cognitive (beliefs, thoughts) and emotional (feelings, attitudes), but also sensorial, spiritual, social and physical elements (De Keyser et al. 2015) of assessment of value and quality of all attributes of customers’ direct and indirect interactions with the company on an overall, dimensional, and attribute level. Each level drives the perception of the level above, rather than evaluation against benchmarks or expectations.

2.5 Customer Lifetime Value Role in Customer Experience Construct

As Customer Experience can be considered as a part of a satisfaction-profit chain, the valuation should also be reflected. Good Customer Experience leads to higher and more stable revenue, lower customer attrition and lower cost of service. The concept of solving the valuation of the customer calls Customer Value Management (CVM). CVM, similarly to Customer Experience, adopted a multidimensional approach to decision making as a part of analytical CRM, but with an integrated approach managing the value provided by a customer (Stirling 2000). Among the CVM methods focusing on the individual customer belongs the strategically oriented Customer Lifetime Value (CLV). CLV is according to Pfeifer, Haskins and Conroy (2005) and Fader (2012) understood as *“the present value of the future net cash flows associated with a particular customer”* (Jašek, Vraná, Šperková et al. 2018). CLV is a predictive metric, and the value is predicted for the customer’s lifetime. Many approaches to counting CLV emerged during the years. The author deals with the CLV problematic more in her previous research (Jašek, Vraná, Šperková et al. 2018, 2019a, 2019b).

The value chain for CLV in (Gupta & Leihman 2008) explains the movement from the mental stage to customer behaviour, which can imply the movement from satisfaction to the point of loyalty. While CLV impacts the financial performance of a firm, CLV itself is a consequence of marketing actions. Marketing actions influence customers' attitudes, satisfaction and other mindset metrics, thus Customer Experience, which then impact product-market results, which in turn drive financial performance. Most marketing studies focus their attention on establishing a link between marketing actions such as advertising and sales promotions and customer mindset variables. However, the impact of most mindset measures on CLV or the value of the company is rather unexplored. Some research contends that CLV and customer satisfaction are correlated, and an increase in CLV is a direct result of customer satisfaction (Berger et al. 2006). According to Singh and Jain (2013), WoM should be a part of CLV as it affects the impact of the customer value on the company. In order to make these perceptual measures managerially meaningful and financially accountable, it is necessary to establish a link between these measures and CLV (Gupta & Leihman 2008). Abdolvand, Albadvi and Aghdasi (2015) consider CLV as a mediator variable between organisation performance and customer satisfaction. As Customer Experience is a part of a satisfaction-profit chain where satisfaction is only one element of the construct, this thesis considers CLV as a mediator variable between organisation performance and Customer Experience (see Figure 2.4).

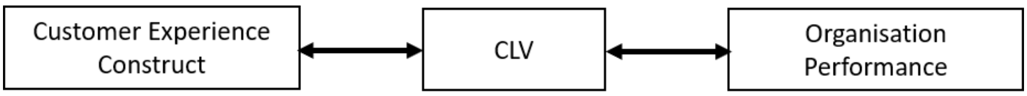


Figure 2.4: CLV as a mediating variable

2.6 Emotions and Personality Traits

As stated in previous sections, the critical element of understanding and managing Customer Experience is the ability to measure and monitor customer reactions to firm offerings, especially customer attitudes and perceptions. These reactions are based on a customer state of mind and determined by customer personality and emotions. Customer experience is a mental concept, and its elements are considered as a perceptual or mindset constructs which comprise aspects of awareness, associations, attitude, attachment, and advocacy (Gupta & Leihman 2008). Chen and Lin (2015) consider human senses, feeling, thinking, action, and relation as the five main elements of Customer Experience.

The feeling is a subjective representation of an emotion. According to Plutchik (2001), emotions are feedback processes. The feelings tend to be followed by impulses to action, thus customer behaviour. Therefore, satisfaction is expressed through customer behaviour and has an emotional and evaluative nature. Evaluation always means expressing emotions and emotions usually have an evaluative nature (Veselovská 2017); therefore, this thesis uses these term interchangeably.

Researchers have recently suggested the need for more attention on emotional aspects of customer relationships (Verhoef & Lemon 2016) and have begun to measure constructs such as passion and intimacy (Bügel, Verhoef & Buunk 2011; Yim, Tse & Chan 2008). Relationship marketing theory extends the focus of Customer Experience to include emotions and perceptions associated with the experience.

The emotions, opinions and their sentiment of the customers can be observed by capturing using their writings, facial expressions, tone and rhythm of the voice in a speech, music or movements. This thesis is aimed at textual expressions of customers with the use of methods of textual sentiment analysis described in Chapter 4 and does not consider non-linguistic emotional means. The language people use to express themselves provides a window into how they feel, how they think, and how they are built psychologically.

2.6.1 Emotions

Emotions are an important factor in influencing Customer Experience. Emotional and factual appeals cannot be easily separated. Customers' emotions can damage or improve customers' perception of the overall experience. Customer Experience visionary Bruce Temkin claims that emotions drive loyalty[9]. Current Customer Experience Measurement focuses more on metrics that reflect a rational or cognitive evaluation of experiences instead of discrete emotions contained in affective responses. There is a research gap in defining critical emotions and experience metrics that have a substantial impact on customer relationships.

Emotions and affective states are pervasive in all forms of communication, including textual VoC. They are increasingly recognised as essential to understanding the full meaning of communication, or the impact it will have on others. Different theories interpreting affective phenomena are comprehensively reviewed in (Davidson, Scherer & Goldsmith 2003).

According to the Appraisal Theory, developed by Martin and White (2003), an **appraisal** is divided into three domains: **attitude**, **engagement,** and **graduation**. Whereas **attitude** is concerned with emotional reactions, **engagement** deals with sourcing attitudes in

[9] http://www.mycustomer.com/marketing/data/what-is-emotion-analytics-and-why-is-it-important

the discourse. **Graduation** is defined as intensifying feelings. The **attitude** is then divided into the **affect**, **appreciation** and **judgment**, depending on what kind of meaning the speaker uses. **Affect**, according to affective neuroscience (Fox 2008), encompasses terms used to describe the topics of **emotions**, **feelings**, and **moods** together. **Emotion** is a discrete and consistent response to the event with an exact significance for a person; **feeling** is then a subjective representation of emotions. Both have short-term duration, unlike **mood**, which is a diffuse affective state that is usually less intense than emotion, but with a longer duration.

Even with clarification of the above terms, research in computer science uses the terms emotion, feeling, mood and affect interchangeably, and they are some controversial issues whether individual human states should be classified as an emotion. During the time, theorists proposed sets of basic emotions (see Table 2.1 for comparison). Basic emotions refer to those that do not have any other emotion as constituent parts. They can be universally recognised (Ekman et al. 1972) by humans all over the world regardless of their race, culture, and language (Yadollahi, Shahraki & Zaiane 2017). Ekman (1992) further expanded the basic set of emotions by adding twelve new positive and negative emotions. Plutchik (1980) arranges basic emotions on four bipolar axes: joy vs sadness, anger vs fear, trust vs disgust, and surprise vs anticipation. These emotions are primary in Plutchik's Wheel of Emotions, where they can be mixed to create new emotions. Shaver et al. (1987) modelled hierarchy with six primary emotions with more than a hundred other clustered secondary and tertiary emotions. In a model of Lövheim (2011), three hormones, serotonin, dopamine, and noradrenaline, form three dimensions of a cube, where each primary emotion is positioned on one of the corners.

Table 2.1: Comparison of Emotions Models

Emotion	**Ekman et al. (1972)**	**Plutchik (1980)**	**Shaver et al. (1987)**	**Lövheim (2011)**
Anger	X	X	X	X
Anticipation		X		
Disgust	X	X		X
Distress				X
Fear	X	X	X	X
Interest				X
Joy	X	X	X	X
Love			X	
Sadness	X	X	X	
Shame				X
Surprise	X	X	X	X
Trust		X		

The emotions can be positive, negative, and some can be both regarding the situation the person feels (interest, surprise, anticipation). The universal emotions in all models from Table 2.1 are anger, fear, joy, and surprise, but there is no agreement on the others. However, the number of negative emotions outweighs the number of positive ones. Although there is no consensus on which model more accurately describes the set of basic emotions, the model proposed in (Ekman et al. 1972) is the most widespread in the field of computer science research.

People use verbal cues instead of nonverbal cues with an equally effective affinity to convey relational information in the Internet environment (Walther, Loh & Granka 2005), and with a more substantial portion of relational information that they would use in face-to-face environments (Yadollahi, Shahraki & Zaiane 2017). This simple theory can be proof of the validity of a textual emotion mining to determine customer emotions. The topic of mining emotions from textual VoC is further discussed in Chapter 4.

2.6.2 Personality Traits

Personality indicates the characteristics and traits that make an individual unique (Goldberg 1990). There are two widely accepted personality models: the Myers Briggs Type Indicator (MBTI), the four-factor model (Myers 1962) and Big Five, the five-factor model (McCrae & John 1992). Big Five has emerged as one of the most well-researched and well-regarded measures of personality structure in recent years, and it led many psychologists to accept the Big Five as the current definitive model of personality (Adali & Golbeck 2014). The Big Five model indicates that personality consists of five dimensions: openness (e.g., adventurous, curious, imaginative), conscientiousness (e.g., reliable, self-disciplined, ambitious), agreeableness (e.g., sympathetic, cooperative, trusting, kind), extraversion (e.g., optimistic, active, talkative), and neuroticism (e.g., sadness, embarrass, anxious) (McCrae & John 1992). A person has assigned a score for each of the five personality factors, and together, the five factors represent an individual's personality (Figure 2.5).

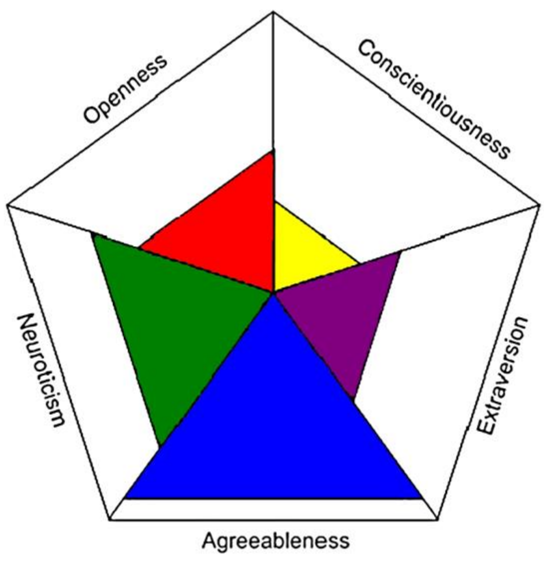


Figure 2.5: Five-Factor Model (McCrae & John 1992)

Personality recognition remains a very active area of research in psychology and has been received attention in computer science and social computing applications in areas such as personalisation and recommendations. Personality traits were found significant incentives in customer behaviour (Liu, Wang & Jiang 2016; Correa, Hinsley & De Zuniga 2010; Amichai-Hamburger & Vinitzky 2010; Selfhout et al. 2010). Prediction of personality can also help in developing effective marketing strategies (Odekerken-Schroder, Wulf & Schumacher 2003; Whelan & Davies 2006).

The traditional approach to assessing an individual's personality concerning a standard taxonomy includes answering questions in a carefully constructed questionnaire. The person's responses are used to calculate a numeric score for each of several factors according to the employed model. However, many personality questionnaires are time-consuming for the person to complete, and difficult for psychologists to standardise and interpret across different languages and cultures (McCollister 2016). The trend is to analyse user-generated content automatically instead of creating questionnaires. The personality influences word choice in writing behaviour, and it is possible to assess personality based on an examination of language samples generated by the customer to the extent that it is possible to characterise the word usage patterns common to the different personality types. Youyou, Kosinski and Stillwell (2015) have proved that computer-based personality recognition is more accurate than human judgments. Microblogs (Golbeck et al. 2011; Sumner et al. 2012), social media (Farnadi et al. 2013; Alam, Stepanov & Riccardi 2013) or blogs (Iacobelli et al. 2011; Oberlander & Nowson 2006) are the most analysed sources of data for personality prediction.

Personality traits and emotions are present during the whole process of Customer Experience, and they are latent to customer satisfaction and loyalty, as it is seen in Figure 2.3. Personality traits have been proved to be long-term stable aspects of individuals, closely related to real-world user behaviour. Even though personality traits are determinants of behaviours, they are somewhat latent constructs activated by situational incentives which result in a behavioural expression. If researchers would determine customer personality, they would better understand the customer's reactions.

2.7 Chapter Summary

The idea of measurement of overall Customer Experience at each stage of the customer journey for every touchpoint (Lemon & Verhoef 2016) is still in an early phase of development, and no secure Customer Experience rigorous assessment of metrics that should be collected have been developed. Existing scales (e.g. Brakus et al. 2009; Klaus 2015) are aimed at specific research and does not understand them as a part of the data model.

Organisations tend to measure specific aspects of Customer Experience such as customer perceptions for a single transaction at a point in time, or as an overarching perception. Customer satisfaction is dominant customer feedback for measuring perceptions; however, it typically does not capture the full Customer Experience. The measurement of Customer Experience is currently dependent mostly on the evaluation of single metrics such as Net Promoter Score (NPS). Multiple share-of-mind metrics predict customer behaviour and future performance better than single metrics and should be combined within the Customer Experience. These metrics should focus more on perceptions and attitudes to gain a comprehensive understanding of customers from their perspective.

The research on customer loyalty, satisfaction, or behaviour focuses more on structured VoC data or manual evaluation of textual VoC data (see sections 2.2 and 2.3). Customer Experience research mainly emphases quantitative metrics like the amount and importance of reviews and their impact on sales expressed in quantitative indicators instead of metrics based on the text itself. However, researchers started to pay attention also to the content of the text, and in latest years, they apply aspects detection techniques to analyse online reviews in textual form for measuring service or product quality, which this thesis considers as a part of Customer Experience construct. The aspect detection techniques are a subject of section 4.5. However, the customer perspective of these analyses is mostly missing.

The data for measurement of Customer Experience elements are collected mainly separately in surveys and directly evaluated at the end of the customer journey, or the evaluators extract necessary data for specific metric calculation from specific tools or analytical CRM. Analytical CRM focuses due to the character of the stored and processed data on data analysis of customers. Data from analytical CRM are frequently used for data mining or conversely serve the results of data mining models as input to the analytical CRM for determining selection criteria of the target group of the marketing activity. CRM, at least regarding the software and technology offered by various vendors, exists mostly in silos, separately from all the existing solutions about textual VoC, which leads organisations to incorporate text analytics into their customer relationship management programs outside the CRM solutions (Reamy 2016). Although companies typically possess much quantitative CRM data on customer buying habits and classifications, there is little knowledge about the emotions of these customers and their evaluations. Customer Experience is more complicated than simple CRM metrics alone (Zaki & Neely 2019).

VoC, mainly in the textual form, is a valuable source of perceptions and attitudes to inform Customer Experience improvements and to track the results of the improvements. Text analytics of VoC enables the use of unstructured text, which brings the Customer Experience Measurement a new dimension of understanding why customers behave and say things the way they do. Generally, structured data are used to answer what questions while text analytics of unstructured text answers why questions.

The thesis stresses the importance of measurement of emotions (section 2.6.1), personality traits (in section 2.6.2), and sentiment detected in textual VoC as these elements of Customer Experience accompany customer's entire journey. They are the main drivers of customer behaviour, and their determination can recognise behavioural patterns. The sentiment analysis is discussed further in Chapter 4.

Customer Experience can be understood in its holistic conception as a demonstration of experience through different elements of Customer Experience, which originates in customer itself. It encompasses cognitive, emotional, and social characteristics, as well as the user's quantitative interaction with the company (Verhoef et al. 2009). It is also an instrument to improve the value of customer and company. From the second follows that the experience can be managed through the measurement of the elements connected as antecedents, succedents, or as parallel constructs to Customer Experience. Their relationships author explained in sections 2.2 - 2.4 and graphically depicted in Figure 6: Customer Experience Construct (deliverable *D1a*). The relationship of the construct with the organisation performance is explained in section 2.5. The construct captures an iterative and dynamic character of Customer Experience. The construct serves as an initial building block for the design and construction of Customer Experience metrics and indicators (deliverable *D2*) and adjacent Customer Experience data model (deliverable *D1*) integrating the information from textual data with structured customer data in Chapter 5.

Chapter 3

Qualitative Research on Use of Voice of Customer in Organisations

This chapter presents qualitative research conducted on a sample of Czech organisations operating in the B2C relationships within the Internet environment. Research in this chapter was published in the article (Šperková 2019). In addition to the literature review in Chapter 2, the author has conducted preliminary research to determine the approach of the organisations to the collection and analysis of VoC in the measurement of share-of-mind metrics as constituent elements of Customer Experience. From the literature review, the research follows the connection between the VoC and Customer Experience and its constituent elements. The literature also indicates the need and importance of more in-depth analysis of textual VoC for the improvement of Customer Experience as it uncovers the insights to customer understanding necessary to deliver a better experience through different channels. Research in this chapter improves the current knowledge and setting of VoC in Customer Experience and its measurement and management in a real business setting. Together with the previous literature review, this chapter answers the research question *RQ1: What is the current situation in the use of Voice of Customer within the Customer Experience Measurement?*

3.1 Methodology

To find out the methods used in practice, the author chose the qualitative research in the form of a focused interview to gather data instead of first intention to conduct a broad quantitative formal questionnaire survey. The pilot testing of the questionnaire survey on a sample of e-commerce companies revealed the lack of theoretical knowledge of respondents in chosen terms. The testing led to a low return rate of responses as the questions needed to be further explained for a complete understanding of the topic. The lack of understanding of the issue may also create a room for errors in responses, and the results may not be relevant. The former questionnaire with the accompanying text that was submitted to the responsible persons in organisations is attached in Appendix A.

The process of the focused interview (Merton 2008) systematically and thoughtfully followed qualitative research in accordance with (Yin 2009; Molnár et al. 2012; Myers 2013). The beginning of each interview was strictly structured and focused on categorisation questions based on the prepared questionnaire survey with a full explanation of the meaning of the question. These questions may be further quantised in interview results. As the targeted-focused interview may lead to bias due to poorly articulated questions (Yin 2009), the author left space for open-ended questions to gain the full view of the participant and new knowledge which led to additional questions. Interviews were conducted between February 2017 and December 2018. Every interview took about 30 - 45 minutes. Results of this research are not guaranteed to be representative of the population but bring in-depth qualitative insight into the environment of Czech B2C companies operating within the internet environment. Gained statistical data from structured questions are intended to be used for descriptive and non-inferential purposes.

3.1.1 Thematisation of the Interview

The 2018 research of Hotjar[10] (Peralta 2018) conducted with two thousand of Customer Experience professionals around the world showed that only 12% of companies identify themselves as mature in Customer Experience. According to the literature review and research conducted by Schmidt-Subramanian in Forrester from 2014[11], surveys are still the dominant source of VoC, and only 29% of organisations use social media. The report shows the immaturity in the field of VoC programs where companies are not able to use VoC to inform Customer Experience design decisions. The report also points to the issue of missing integration with the other processes and knowledge in companies.

Based on the Forrester research from 2014, the author aims to explore the situation of analysis of customer textual data and its connection to the Customer Experience Measurement within the Czech environment. Thematisation of the focused interview emerged from the structured questionnaire and resulted in a list of essential information that needed to be gathered:

1) The current extent of analysing VoC in B2C organisations in the Czech Republic about Customer Experience
    - Evaluation of Customer Experience elements and their reporting
    - Understanding the concept of Customer Experience
2) The current situation in analysing textual VoC in B2C organisations in the Czech Republic
    - Sources of textual VoC

[10] Available at https://www.hotjar.com/blog/customer-experience.
[11] More information at https://www.forrester.com/report/The+State+Of+Voice+Of+The+Customer+Programs+2014+Its+Time+To+Act/-/E-RES115913.

- Evaluation of textual VoC

3) The barriers to adopting the full potential of analysing VoC within Customer Experience and its management

As the author also asked structured questions based on the questionnaire, responses were also quantified.

3.2 Interview Participants

The author initiated the selection of interview participants through electronic communication. The addressed contacts were collected in previous research in Customer Lifetime Value (Jašek, Vraná, Šperková et al. 2018, 2019a, 2019b), in pilot testing of the questionnaire survey gained by professional social network LinkedIn, and in analytical communities. Interviewed participants recommended others. The requirements for the participated organisations include:

1) operating in the B2C relationships,
2) operating within the Internet environment,
3) existing analytical intentions (Business Intelligence, Customer Intelligence, marketing analytical department or similar) within the organisation,
4) a capability of assessing the status of the analytics according to the interview context.

The participants who were interviewed for the organisations had to be in a role of organisation owner (CEO), marketing analyst, BI / CRM analyst or a manager or executive of staff in these roles to qualify for an interview. The communication was conducted in person or through electronic channels (instant messaging, Skype) in a real-time manner in the Czech language. Interviews were conducted between June 2016 and December 2018.

The focused interviews were conducted with representatives of 25 organisations. Due to confidentiality agreements, personal or sensitive business information is not provided within the results of the research. 52% of respondents are in business for more than ten years, 20% between two and five years and 20% between five and ten years. The rest 8% are newcomers in the market. Except for four participants who have their central location outside the capital city, the organisations have their headquarters in Prague. The most represented industry in the interviewed sample is retail and e-commerce (15 respondents). 24% of organisations operate in finance and banking, and the rest are represented by one in healthcare, IT security, consulting to end customers and providing SaaS. 28% of participated companies have more than a thousand employees, 24% have between 250 and 1000, 28% have 50 to 250, and the rest have less than ten employees. Only one company has 10 to 50 employees. 55% of organisations serve to hundreds of thousands of customers, 32% have tens of thousands of customers, 9% have 1000 to 10 000 customers, and only one company have less than thousands of customers. From this sample, nine organisations are in business for more than ten years, with hundreds of thousands of customers and more than 250 employees. Except for the SaaS provider, these nine organisations contain representatives from all mentioned industries and can be considered as large well-established organisations.

3.3 Interview Results

According to thematisation of the interview, three key topics formalise this research: 1) The current extent of analysing VoC, 2) Current situation in analysing textual VoC, 3) The barriers to adopting the full potential of analysing VoC within Customer Experience. Key findings are described in the same manner and order. Conclusions were generalised if similar answers appeared in a majority of interviews. Gained statistical data are also presented.

3.3.1 The Current Extent of Analysing VoC in Organisations in Relationship to Customer Experience

From the interviewed organisations, it can be concluded that VoC plays a more or less important role in measuring and managing the Customer Experience. Only two from 25 interviewed organisations do not measure any share-of-mind customer metrics and do not engage in the evaluation of VoC even in a structured form. In line with literature research, customer satisfaction is the most measured metric in organisations (80%), followed by customer behaviour (64%) and customer loyalty (60%) – see Graph 1. 64% of companies also agree that they measure Customer Experience, but the understanding of the conception is different in companies. Some respondents understand experience as a satisfaction – *"Satisfied customer who wrote a positive review."* The company from the healthcare industry understands Customer Experience rather like User Experience: *"Our Customer Experience is clear - we usually monitor the side effects of the medicaments, and then we attach it to the package leaflet."* In retail and e-commerce it is common to understand experience as a classic expectation-disconfirmation construct: *"When the customer buys, and the purchase arrives on time, and he finds everything there is to be, it is a good Customer Experience, which is reflected by the customer giving a good review."* Other participant said his company is deeply involved in Customer Experience during the entire customer lifecycle: *"For example, when a customer calls to customer support, we track what issue or requirement he has and if something happens after this call. We also make different incentives in the e-shop and track* *customer reactions to these incentives."* The other representant of the smaller company selling experiences concedes they read only satisfaction reviews to the products they sold and admitted *"But it does not say anything about the satisfaction with our websites, the purchase process, call-centre, reservations or availability of terms. We would need to define KPIs and measures and analyse them to have a comprehensive view of a customer."*

When the authors asked differently, if organisations collect VoC for measuring comprehensive Customer Experience, the number of positive answers dropped to 36%. That means, 28% of companies measure Customer Experience only with the help of hard structured numeric data like delivery time, number of purchases, the elapsed time between two purchases and similar.

According to respondents in the interviewed sample, only two organisations measure all mentioned (Graph 1) share-of-mind metrics, which are constituent elements of Customer Experience in the manner this thesis understands it. Both organisations come from the financial and banking sector, with more than a thousand employees. Customer personality traits measure in some way four organisations, seven organisations determine emotions, and six organisations detect sentiment. 52% of respondents claim that these measures are parts of their more comprehensive view of the customer within periodically monitored complex dashboards. Other 48% of companies perform only on-demand, ad-hoc reporting designed to specific needs of stakeholders. In the manner of the definition of Customer Experience in section 1.1, only three studied subjects could be classified as active adopters of Customer Experience – two from the financial and banking sector and one from the retail environment. Although the approach to analyses in the retail company could be significantly improved; the company understands the conception according to Lemon and Verhoef (2016) and Buttle and Maklan (2015) from section 1.1.

Graph 1: Number of organisations measuring mentioned share-of-mind metrics (25 respondents)

The satisfaction is mostly measured in companies by the popular NPS metric and qualitatively with customer surveys in the form of a questionnaire or on-site surveys, but open-ended questions are usually evaluated manually. Complaints and customer issues are also highly monitored. Organisations track purchases, retention rate and customer churn, the share of turnover costs, product portfolio, cancellations or damages to the client among the quantitative metrics. In general, companies analyse structured, customer behavioural data primarily through web analytics with tools such as Google Analytics,[12] or Hotjar,[13] or extract data from their ERP/CRM databases. The company that sells software as a service tracks application usage and interactions to determine behaviour, engagement, and ratings from the support team to evaluate satisfaction. Some companies perform usability testing.

Companies generally claim that they evaluate VoC to meet customer needs and desires better and to become more customer-focused. Other reasons are marketing purposes – to know which channels to allocate the budget for marketing communication. Participants admitted that optimising resources on advertisement through digital marketing channels is one of their essential analytical goals. However, there is no consensus on the right approach, and different companies use various sources of data and models to measure attribution. Evaluating of VoC also helps companies with the identification of opportunities for innovations, product and service planning, and developing new business opportunities. In some companies, the evaluation of VoC also enhances the work system and workflow improvements that are directly related to the employees' efficiency and satisfaction.

An interesting finding has emerged regarding the financial and banking industry. The maturity of Customer Experience management and analysing VoC does not correlate with the size of the company and its presence in the market as one would suppose. One participant answered that they do not measure share-of-mind customer metrics at all; the other two banks do not even collect textual VoC. On the other hand, the most matured organisation in evaluating VoC and text analytics usage is a large financial institution. The institution claims to have consolidated Customer Experience system to measure all share-of-mind metrics, including detection of sentiment, emotions, and customer personality. However, these elements of Customer Experience are not the goal of analysis with text analytics. They use different channels for this measurement from many VoC sources, including social media feedback, feedback from open innovation platforms, and focus groups. Next to regular agency measures like NPS, they have back-end analytics operating by the whole department of data analysts, which is further reported regularly in complex dashboards and spread through the

[12] More information at https://analytics.google.com/analytics/web/.
[13] More information at https://www.hotjar.com/.

whole company. It should be noted, that the company has considerable resources to invest in innovation and analytics as with more than a thousand employees it operates in the market more than ten years to more than hundreds of thousands of customers.

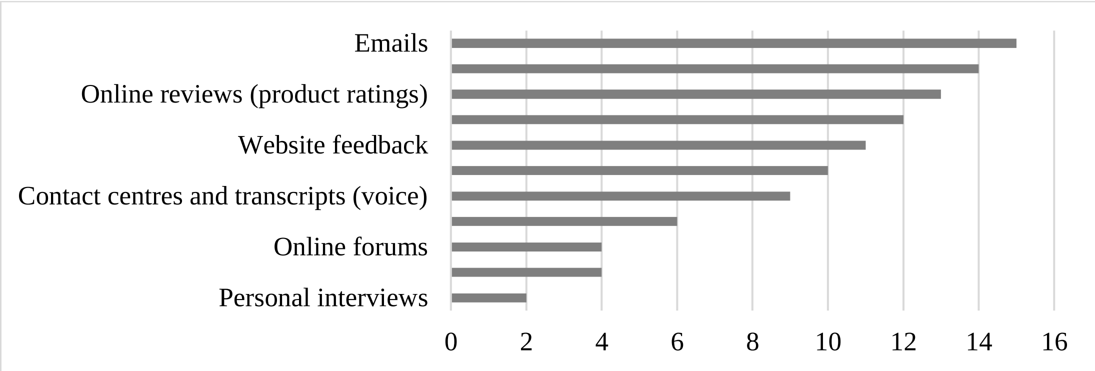
3.3.2 The Situation of Analysing Textual VoC in Organisations

Only 36% of interviewed respondents answer that their organisation collects and automatically analyse customer textual data with text analytics. Another 40% of organisations analyse collected textual VoC manually. 12% of companies collect some sources of textual VoC, but do not further analyse them. 12% do not collect textual VoC at all. Three largest organisations in the sample admit that next to the sophisticated automatic solutions, they still analyse the text manually. Some companies use the help of specialised tools for building customer surveys, but this software is unable to analyse textual data and offers only basic counting of answers which cannot be considered text analytics. Another large company is involved in the proof of concept with a commercial text analysis package. 20% of companies analyse their textual VoC data automatically with their in-house tools or solution, 12% of organisations depend on consulting vendor or/and technology supporting these analyses in addition to the internal solution or bought special software package for text analysis, two of these depend entirely on external sources. One company analyses text with the help of open-source and free software.

Table 3.1: Collecting and analysing textual VoC in organisations (25 respondents)

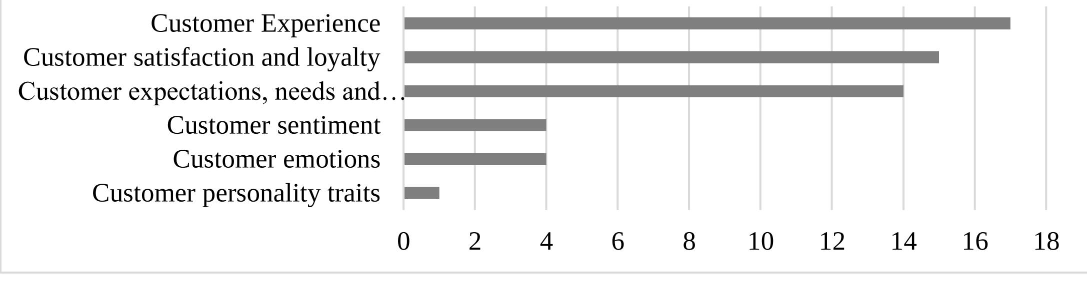
Organisations collecting textual VoC and automatically analysing data with text analytics	6
Organisations collecting textual VoC and analysing manually	10
Organisations collecting textual VoC and analysing both manually and automatically	3
Organisations collecting textual VoC without further analysis	3
Organisations not collecting textual VoC	3
From organisations analysing automatically: (organisation may fall into several categories)	
Organisations using an in-house solution	5
Organisations dependent on vendors	3
Organisations using free software	1

Market and customer surveys are still the dominant sources of textual feedback from customers, even in Czech companies (63.6% - see Graph 2). *"In general, we prepare surveys to analyse the market (before the release of new product, service or benefit). We also have some external sources to see how the customers/public perceive our company."* Companies use dedicated software to build and evaluate customer surveys, but dedicated software usually cannot help with in-depth analysis of open-ended responses in textual form. 68% of companies also collect emails from customers; although not all of them have the knowledge and tools to analyse the textual content automatically. Emails are a more accessible source of VoC than surveys; they serve mainly as a source of requirements and complaints: *"Serious internal reports are related to complaints"*. Other important sources of VoC are customer reviews (59%) (also in price comparison systems) and social networks (54.5%), followed by website feedback, chat, calls to contact centres and their transcripts. Not very popular sources are blogs and microblogs, online forums, and product ratings. Only one respondent admitted that they collect information from the personal dialogues with the customers during their visit in the store and one participant replied that their company is involved in ethnography, visiting customers at home and conducting in-depth interviews. Only 32% of organisations collect textual data from more than four sources. Three companies do not collect any textual data.



Graph 2: Number of organisations collecting mentioned sources of textual VoC (22 respondents)

77% of those who analyse in some way textual VoC stated that they do it to manage Customer Experience (see Graph 3). 15 of 22 of those participants who analyse textual VoC contended they analyse textual data to measure customer satisfaction or loyalty, and 14 to detect customer expectations, needs and requirements. Three companies look in the text for sentiment and emotions together, while the other four companies look either for sentiment or emotions. Only one organisation extracts personality from the text.



Graph 3: Number of organisations determining or measuring the mentioned elements in textual VoC (22 respondents)

When analysing text automatically or manually, companies looking in text mainly for topics and themes or named entities like locations, people, companies, products and similar. *“The main purpose of the textual data analysis we do is to alert us when a specific term or topic starts appearing in the text so we can identify potential problems and act as fast as possible. However, we are not really grouping and looking at the data regarding the categories you describe."*

Interestingly, more only manually analysing companies (60%) try to extract relationships and facts from the text than the automatically analysing companies. It is a time-consuming task when they need people reading every single contribution. Abstract groups or entities analyse 40% of the automatically analysing companies. Five of all companies extract metadata from customer contributions. Currently, five companies try to extract sentiment, opinions, attitudes, perceptions, emotions, and intents automatically. One respondent from the financial sector answered that social networks are essential for detecting emotions and have a high priority in text analytics. This company analyse manually and has a dedicated employee to reading social networks. Only two companies automatically extract semantic annotations in text. Only one company mentioned that it analyses the VoC in multiple languages as it has international customers.

3.3.3 Barriers to Achieving the Full Potential of Analysing VoC within Customer Experience

Despite the known potential of analysing VoC and its contributions to better Customer Experience and its measurement and management, only a few companies achieve its full potential. The identified barriers and issues to meet the potential in respondents’ answers are:

1) **Sharing VoC insight across the organisation**: The main issue of analysing the VoC is that the results are rarely spread through the organisation, but serve to only a handful of employees, usually in the marketing department or on demand of management, and they are not broadly embedded in the organisation. The analysis of share-of-mind metrics usually depends on a dedicated small team, often only one or two employees in smaller companies, or department in larger organisations. The gained insights are rarely used for employee incentives and performance reviews. Only 52% of interviewed companies involve the share-of-mind metrics into a comprehensive view in the form of sophisticated dashboards which are periodically updated. The rest realise ad-hoc reporting based on their actual needs or tailored to management’s request. Some respondents assert that the departments in the organisations are so overwhelmed with their own KPI’s and problems that they are not ready to embrace the Customer Experience program.

2) **Struggle to prove financial results**: Organisations know the value of analysing VoC for Customer Experience. However, more than half of respondents do not track any revenue impact or cost savings resulted from their efforts, so they do not precisely recognise the financial value of their intentions. The lack of financial results is also the reason why the evaluation of share-of-mind metrics and some textual analytics incentives do not take priority in the company pipeline. Less than half of organisations get active executive support for their efforts as the priorities are elsewhere. Smaller companies, in particular, focus on quantitative revenue metrics.

3) **Textual VoC is not profoundly analysed**: 24% of the interviewed companies do not analyse textual VoC, and from those who do that, more than half still analyse manually. They do not have the tools to integrate customer textual data from different channels into a single location to analyse and identify the findings relevant and accessible to employees across the company.

4) **Fragmented view of the customer and missing integration of data:** Companies track customer journey on companies' websites using web analytics tools, but they are unable to analyse Customer Experience across the customer's entire journey across all channels. Only a few companies can extract VoC and expand its analysis results across channels and departments in the organisation. Larger companies use their CRM systems for a customer-centric view. Same as web analytics tools can describe customer journey through the company's website, consolidated Customer Experience Management can go beyond and measure experience at every touchpoint the customer interacts. Various departments in the company, primarily the medium to a large one with more than 50 employees, use different tools for different channels, so the reports from these tools are also not consolidated. Most of the monitored metrics, such as retention rate, measure Customer Experience from the perspective of the organisation based on aggregated customer data rather than individual customer perspective.

5) **A missing action with individual customers:** Almost one-third of respondents admitted that they leave their insight without a direct action to the individual customer, which is so crucial in today's one-to-one marketing. Smaller companies and newcomers with fewer customers, where every customer is a critical intangible asset, and each requirement is manually processed, are better in this individual approach. The larger organisations with more customers and without automatic processing of requirements are not always able to approach the customer

individually. *“We stick to the principle of ‘first response solution’ when we want to handle the request with the first answer to the customer. We also track the top tenth decile at the longest speed of customer tickets resolution, which means that we track the solution time of individual requirements and focus on cases that took the longest time for their resolving. After, we solve which department is responsible for the specific case and what is the exact content of that case.”* This approach is very reactive, which would not be wrong if it were not selective for only the worst cases. Companies need to establish a proactive mechanism for responding to either positive or negative feedback on the base of customer sentiment and not based on quantitative response time measurement. Only 41% of organisations with text analytics automatically determine customer sentiment in text. Some companies also ask customers to fill their surveys but leaving their feedback without a reaction, which leads to unresolved problems and missed opportunities. Respondents also admit that their efforts almost always serve for reporting but missing the effectivity in driving actions. *“In our company, three employees handle orders and solve customer problems through different channels – email, chat, calls. They handle everything manually, and in seasonal peaks, they are overwhelmed with requirements. We would be happy for some solution which would be able to sort the requirements automatically and enable employees to react faster.”*

6) **A missing formalisation of the processes:** Companies generally lack the formal processes in managing Customer Experience. Reports need to be more feasible and require regular review of metrics, metrics owners, and problem prioritisation. Only three of the interviewed companies reached this maturity.

3.4 Chapter Summary

Results of the interviews show no consistent definition of the concept of Customer Experience. Few companies share the general idea of the concept in the way this dissertation describes it. However, they are far from fulfilling its measurement. Most of participating organisations understand Customer Experience generally as customer satisfaction during the purchase phase of customer lifecycle but not beyond it. The current extent of analysing VoC in organisations in relationship to Customer Experience is described in section 3.3.1.

From the research follows that companies are not fully entrenched in analysing VoC with text analytics. The situation is described in section 3.3.2. VoC is vital for improving Customer Experience, but companies are not able to realise the full potential of the resources of information. A great deal of the textual VoC is still not entirely used in organisations, so even though companies are mainly successful in gathering this data, they fail in an in-depth analysis of the feedback with advanced text analytics capabilities and further actions from the insight they generate in their business. Several barriers to achieving the potential of the analysing textual VoC within the Customer Experience Measurement were identified in the respondents' answers (see 3.3.3). The further text will refer to these barriers by their numbering (barrier 1-6). Majority of participating organisations demonstrated missing utilisation of Business Intelligence to understand Customer Experience.

One of the goals of the Customer Experience data model and related measurement designed in Chapter 5 is to mitigate these barriers to gain a thorough insight from textual VoC within the Customer Experience. One of the participants from this research agreed to be a subject of validation of the artefact. This middle-sized e-commerce company does not currently have a comprehensive overview of Customer Experience and is dedicated to ad-hoc reporting only. The maturity of the Customer Experience of this company and the specific goals of its stakeholders is further explained in treatment design in Chapter 6.

Chapter 4

Analysing the Content of Textual Voice of Customer

Customer’s opinions play a significant role in the decision process. These opinions are contained in VoC. Analysing of VoC requires a combination of psychology, marketing, sociology, cognitive science and due to the textual expression – text analytics. Text analytics characterises the content of the unstructured text by subject matter - major and minor topics and by positive and negative sentiment or emotions. Therefore, opinion mining, sentiment analysis, emotion mining and aspect detection methods explained further in this chapter fall under the term of text analytics.

This section is extending the previous knowledge of VoC role in Customer Experience and serves as a theoretical introduction to the problematics of text analytics, mainly sentiment analysis and aspect detection. Due to enormous and still growing scale of textual VoC data in Web 2.0, there is more emphasis on the automatic approach of analysis of its content. Automated analysis can lead to higher reliability of detection of specific information from VoC, as well as greater possibilities to handle large amounts of textual data. In the case of structured VoC data, automatic analyses are well developed in the form of data mining. Data mining of structured data enables to understand customer behaviour patterns. VoC, in its textual form, allows to understand the customer himself and focus on his individuality.

Early marketing attempted to track the number of mentions which the company or its products received from its customers. In the next stage, researches used simple text mining world counting and automatic topic detection based on clustering and simple term frequency. Text mining has an established set of methods, well described in (Feldman & Sanger 2007), which derives many procedures from data mining. Further, sentiment analysis was introduced to address the sentiment of the written text. This chapter discusses different approaches and techniques used in sentiment classification research. Aspect detection techniques are discussed in section 4.5. Emotion mining and personality traits detection methods are described in section 4.6.

The treatment design and validation of this thesis are performed on textual data in the Czech language. Therefore, the current state of sentiment analysis in Czech is reviewed in section 4.7. Section 4.8 describes the current attempts of integration of textual VoC into Business Intelligence processes as BI is a vital instrument of the Customer Experience Measurement in a way the author understands it as a multidimensional data model. In section

4.9, the author suggests CRISP-DM as the methodology for text analytics processing and validates it for the purposes of VoC integration to Customer Experience.

The goal of the chapter is not a detailed explanation of how individual algorithms work, but rather a simplified overview, as there is an enormous amount of techniques and their adjustments. The traditional approaches to sentiment analysis and the evolution of the field are comprehensively discussed in monography "Sentiment Analysis" by professor Bing Liu[14] (Liu 2015). The Chapter contributes to the objective *O3*; sections subsequently serve as a guide for the selection of methods and techniques performed in Chapter 6 (deliverable *D3*). The criteria for text analytics methods applicable to mining the Customer Experience elements are defined in section 4.2. The chapter was created together with Chapter 2 in the second half of the year 2016 and early 2017 with minor editing in 2019. The chapter also refers to the previous author's work.

4.1 Sentiment Analysis, Opinion Mining and Emotion Mining

In literature exist inconsistencies between the terms of sentiment analysis, opinion mining and emotion mining. Many types of research understand opinion mining and sentiment analysis as the same approach, and under the term of opinion mining also classify emotion mining. *Sentiment analysis, also called opinion mining, is the field of study that analyses people's opinions, sentiments, appraisals, attitudes, and emotions toward entities and their attributes expressed in written text (Liu 2015)*. Opinion Mining originates from the information retrieval community and aims at extracting and further processing users' opinions about products, services or other entities (Dave et al. 2003). Sentiment analysis was initially formulated as the Natural Language Processing task of retrieval of sentiments expressed in texts (see Pang & Lee 2008). In literature, this process is also known as subjectivity analysis or appraisal extraction (Pang & Lee 2008; Tsytsarau & Palpanas 2012).

Contrary, Yadollahi, Shahraki and Zaianne (2017) claim that opinion mining and emotion mining fall both under the term of sentiment analysis and they divide it into two branches because they understand sentiment as an opinion or idea coloured by emotion. Analysing the sentiment of a unit of text can encompass investigating both the opinion and the emotion behind that unit. Opinion mining deals with the expression of opinions in texts that can be positive, negative or neutral. Emotion mining is concerned with the articulation of emotions (e.g., joy, anger) reflected in the text. The sentiment reflects feeling or emotion, while emotion reflects attitude. In general, the goal of the sentiment analysis is to automatically extract the

[14] Official page of professor Bing Liu available at https://www2.cs.uic.edu/~liub/.

viewpoints of some entities based on subjective data. Author of this thesis sticks mainly with the term sentiment analysis, however, similarly, as in (Liu 2015), this thesis understands term opinion as a broad concept that covers sentiment, emotion, evaluation, appraisal and attitude.

Many tasks can be performed within the sentiment analysis. **Subjectivity detection** detects if given text represents an opinion or a fact, or more precisely whether the given information is objective (factual) or subjective (non-factual). **Emotion detection** recognises if the text conveys any emotion or not. **Sentiment classification** contains **opinion polarity classification**, determining whether the text expresses a positive, negative or sometimes neutral opinion. **Emotion polarity classification** determines the polarity of the emotion in a text. **Emotion classification** then classifies emotions in a text into one or more sets of defined emotions. The answer to a detection problem is binary, which means that there is or is not an opinion or emotion in the text. The answer to a classification problem is then the exact type of opinion (positive, negative) or emotion (happiness, sadness, etc.) (Mishne 2005; Blei & McAuliffe 2008; Strapparava & Mihalcea 2008; Bao et al. 2009, 2012; Rao et al. 2014) of the target text. Between other tasks, not further explored in this thesis, belong opinion summarisation (Hu and Liu 2004), opinion spam detection (Jindal & Liu 2008), argument expression detection (Lin et al. 2006), emotion cause detection (Lee et al. 2010; Gao et al. 2015), comparison-based opinion mining (Jindal & Liu 2006).

4.1.1 Levels of Sentiment Analysis

Sentiment may be distributed all across the processed text at different levels. It is possible to determine the sentiment of entire contributions (**document-level classification**), sentences or entire paragraphs (**sentence-level classification**) or individual expressions represented by words or phrases (**feature/aspect-level classification**). Document-level classification is suitable if the entire text was written regarding one topic (Pang & Lee 2004; Turney 2002). The feature-level classification has the finest granularity and far more accurate results (Liu 2010). The primary objective of feature-level classification is to identify and extract a feature (aspect) and to pair it with the right sentiment word.

The sentiment of the higher level of classification is usually derived from polarity at the lower levels, either by using simple methods as the majority vote or by employing different probabilistic classifiers. The polarity of the sentiment is usually not uniformly distributed across a document. Thus, in recent years the aspect detection (see section 4.5) for a targeted assessment of several aspects of the evaluation texts (Brody & Elhadad 2010; Hu & Liu 2004; Dong et al. 2018) began to be combined with sentiment analysis. According to this concept, the methods of sentiment classification in this thesis are performed at lower levels, and the overall polarity of the higher levels is derived based on the results from lower levels.

4.1.2 The Parts of the Content for Sentiment Analysis

For the VoC analysis, it is essential to define individual pieces of content so that it is evident what is being analysed (see next section 4.2). The textual part of the Customer Experience model in Chapter 5 builds on the following terminology.

Liu (2015) defines opinion as a set of items (e_i, a_{ij}, s_{ijkl}, h_k, t_l), where e_i is the **entity** name, a_{ij} is an **aspect** of entity e_i, s_{ijkl} the **sentiment** of aspect a_{ij} of the entity e_i, h_k is the **opinion holder,** and t_l is the **time** when the opinion was expressed. The entity is the target object of the opinion (**opinion target**); it can be a product, a service, a topic, a person, an organisation, an issue or an event based on the main topic discussed by opinion holder. **Aspect** represents parts or attributes of entities. In some literature, aspect is referred to a **feature** *f*. Then an entity as *e (f)* in document *d* can be defined. The sentiment is positive, negative or neutral, and can be expressed on the different intensity level. Indicators *i, j, k, l* indicate that the items in the definition must match. In other words, an entity *e* is described as a pair (*T*, *W*), where *T* is a **hierarchy of parts**, subparts, and so on, and *W* is a **set of attributes** of entity *e*. Each part or subpart also has its own set of attributes.

The sentiment is the author's belief, opinion or emotion expressed on the target object with the opinion words. This thesis determines emotions as separate elements. Liu (2015) does not mention **opinion** (**appraisal) words,** which are the evaluative elements carrying the sentiment. Appraisal words, mostly adjectives and adverbs, express either a desirable or undesirable state of the opinion target.

The sentiment can be rational or emotional. The **rational sentiment (rational opinion)** is of rational reasoning, tangible beliefs, and utilitarian attitudes with no expressed emotions. The **emotional sentiment** is derived from intangible and emotional responses to entities that go deep into people's psychological states of mind (Liu 2015). Only in emotional sentiment can also be determined specific discrete emotion.

Subjectivity tells if an opinion is subjective or objective. If an opinion is subjective, then it can be determined its **polarity** (semantic orientation) and **intensity** on the rating scale, which corresponds to the positive or negative assessment of the significance of this sentiment. Neutral sentiment has an objective opinion that bears only factual information. A special semantic category – bipolar – which can have both positive and negative sentiment according to the given context is sometimes defined, but that is hardly expressible on any scale.

Liu (2015) also defines entity/**aspect category** which represents a unique entity or aspect, whereas an entity/**aspect expression** is an actual word or phrase that indicates an entity or aspect category in the text. Each entity/aspect or entity/aspect category should have a unique name. The process of grouping or clustering entity/aspect expressions into categories is called entity/aspect **resolution** or **grouping**. Aspects expressions are usually nouns and noun phrases but can also be verbs, verb phrases, adjectives, adverbs, and other constructions. Aspects can be explicit or implicit (Hu & Liu 2004). Explicit aspect expressions are nouns or noun phrases: *"The sound quality of the speaker is great."* The explicit aspect is *sound quality*. Aspect expressions that are not nouns or noun phrases but indicate some aspects are called implicit aspect expressions: *"The speaker is expensive"*. *Expensive* indicates to implicit aspect *price*. Aspect category can group explicit and implicit aspects together.

4.2 Requirements for Text Analytics Methods to Mine Customer Experience elements

The selection of the methods (discussed further in this chapter) for determining elements of Customer Experience is based on the target objects needed to be extracted from the given textual data. These target objects are contained in the customer's opinions and represent entities as objects and their aspects. The elements of the Customer Experience then reflect perceptions of the target objects and (according to the fulfilment of *O2* and *D2*) present

1) **sentiment** expressed about the target objects (positive, negative, neutral) and
2) **discrete emotions** expressed about the target objects (e.g. joy, sadness, trust).

From the overall expression of the customer can be determined

3) **personality traits** of the customer who expressed the opinion (e.g. extroversion, neuroticism).

The selected methods should determine all these subjects of the analysis, which serve further as elements of Customer Experience. The selected methods should meet the three most important criteria according to the analysed element of the Customer Experience:

1) **Satisfaction**: The methods should be able to extract aspects of customer perception and the sentiment of the perception – its polarity and intensity.
2) **Emotions**: The methods should be able to determine aspects about which the emotions are expressed and the emotions itself. The text can be multi-emotional; the method should be able to assign more than one emotion at the same time.

3) **Personality traits**: The methods should be able to assign more than one personality to the customer as the customer is considered to have more than just one personality.

Referring to section 4.1.2, in Customer Experience, the opinion target is an entity which represents the object of the Customer Experience described in the customer textual contribution (comment) as depicted in Figure 4.1. The object can be a product or service, topic, event, person or an issue related to the product, service or company itself about the customers expresses their opinion.

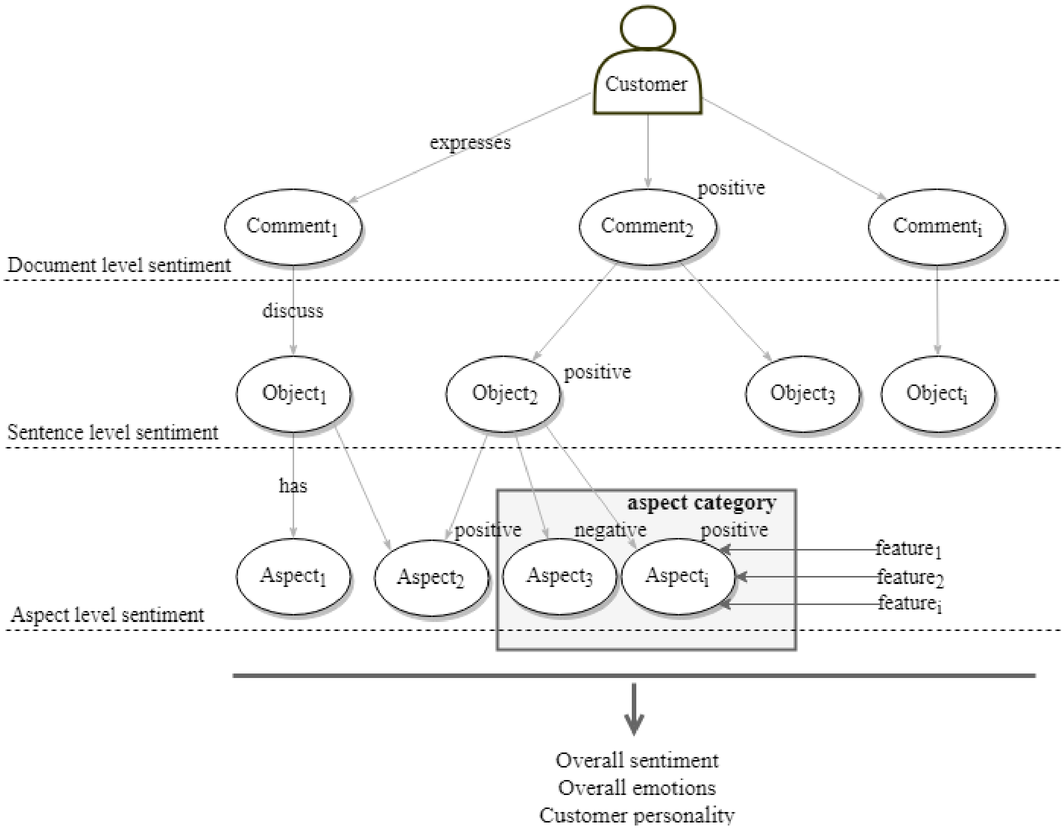


Figure 4.1: The parts of the VoC content from a single customer perspective

The object can be discussed from different perspectives which represent different aspects. These aspects can be product/service attributes (features), components (parts), functionality or the dimensions of quality. For example, if the customer buys a sightseeing flight, the object is the *flight* itself, and aspects can be the *plane* comfortability, *price* the customer paid for the flight, *weather* which was that day of the flight, or the satisfaction with the *pilot*. All these aspects can customer evaluate with different words which some of them carrying the sentiment (appraisal words). According to Song et al. (2016), only the crucial aspects can be considered as features or components.

Some aspects can be close to each other on the same topic. It is desirable to find the aspects of the potential interest and cluster them together into **aspect category** under one term as described in section 4.1.2. This step reduces the number of different aspects with the same informative value. The aspect category is typically more general than the aspect terms itself and does not necessarily occur as a term in the text. Thus, the aspect category can represent either a dimension or quality. For example, if the customer talks about the aspect category *weather*, he can use a sentence like *"It was a beautiful sunny day without any cloud."* The detected aspects are *sunny day* and *cloud*, and both terms fall under the aspect category *weather*. Also, the aspects the customer discusses in VoC are not known in advance. Based on this fact, other criteria for the applied methods arise:

4) Ability to collect words together that reflect topics of potential interest
5) Ability to identify aspects without prior knowledge
6) Ability to group aspects into categories.
7) Ability to determine the aspect's importance and impact on overall satisfaction without further intervention

For the purposes of Customer Experience Measurement, the author is interested not only in satisfaction and expressed emotions about individual objects and their aspects but also overall customer satisfaction. The customer can write many comments; each comment contains opinions about different objects with several aspects. The sentiment and emotions are assigned to every aspect for every object in every subjective comment (if there is some detected). The object's sentiment is derived from the expressed aspects' sentiment; the comment's sentiment is derived from the sentiment of discussed objects in the comment. In different words, the overall satisfaction and expressed emotions are gained from the classification of the lower levels of analysis. This approach is consistent also with the multidimensionality discussed in Chapter 5 and enables to add customer perspective to Customer Experience with preservation of the product perspective by drilling and slicing at lower levels of granularity (for example to measure the average sentiment of a specific aspect of a particular object from the perspective of chosen customer segment).

The personality traits are determined from all the comments the customer has written. More textual data ensures a better prediction of the personality. Determination of the emotion elements is possible only from the subjective and evaluative text with the emotional sentiment. The element of personality traits is also possible to determine from the text with rational sentiment.

4.3 Features Extraction and Selection

The pre-processing task of the input text in text analytics contains the extraction and selection of characteristic features for data and transformations of data into collections of documents. This process is used to identify targeted words and to remove meaningless and unnecessary words. The pre-processing uses methods of natural language processing (NLP) like tokenisation, lemmatisation, stemming and removal of stop-words. The most important features used in this thesis are **Part of Speech** (PoS) assigned to individual words representing its position and role in the grammatical context. **N-grams** represent the presence of the terms, position and their frequency in the document. In combination with PoS, it is possible to build n-grams in the precisely desired structures (bigram adjective-noun, trigram noun-verb-adjective) as a strong indicator of belonging to the class in classification. Other features are **appraisal words and phrases** carrying the sentiment, **negations,** which can change the potential sentiment (sentiment shifters), **homographs**, **synonyms** (concatenated or replaced), **syntactic dependency,** or normalised words correction.

Feature selection is a reduction method. It can be divided into automatic statistical methods and lexicon-based methods that need human annotation. Lexicon-based approaches usually begin with a small set of ‘seed’ words bootstrapped through synonym detection or online resources to obtain a more extensive lexicon. The feature selection techniques treat the documents either as a group of words (Bag-of-Words) or as a string (vector) which retains the sequence of words in the document. Bag-of-Words (BoW) is popular due to its simplicity in the classification process. Features with lowest weight (based on various statistical methods) or words with the highest frequency in the document are then filtered. Recently, another popular method is world embedding with the most used system Word2Vec[15] , which is a computationally efficient neural network prediction model that learns word embeddings from the text. It contains a continuous Bag-of-Words (CBoW) model (Mikolov et al. 2013a) and the Skip-gram (SG) model (Mikolov et al. 2013b).

Between statistical methods belong Pointwise Mutual Information (PMI), Principal Component Analysis (PCA), Chi-square (v2), Latent Semantic Analysis (LSA), Hidden Markov Model (HMM), Latent Dirichlet Allocation (LDA), information gain and Gini index (Medhat, Hassan & Korashy 2014). The feature selection is very tight with aspect detection, which uses the same methods (see section 4.5).

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[15] Source code: https://code.google.com/archive/p/word2vec/.

4.4 Sentiment Classification

Sentiment classification is typically composed of two tasks: (1) identification of expression carrying the sentiment and (2) determination of the polarity of expressed sentiment and its intensity. Three basic approaches can be distinguished in analysing sentiment: Machine Learning approach (supervised, unsupervised and semi-supervised), lexicon-based approach (dictionary-based and corpus-based), and hybrid approach mixing both mentioned.

Approaches based on Machine Learning classification techniques are used to classify the text by finding the candidate that best approximates object based on training data. Lexicon-based approaches assign sentiment scores to opinion words found in the data based on the sentiment defined in dictionaries with opinion words for polarity recognition. Several studies combine these methods to obtain better performance and improvement in sentiment classification. They can achieve the best of both approaches, words stability and readability from a lexicon and the high accuracy of Machine Learning algorithms. Due to a considerable number of techniques, many researchers experiment with different algorithms and compare them with each other on a different type of levels on various features within different datasets. An overview of different opinion mining methods, their accuracies, used datasets, processed features or level of analysis can be found in (Pang & Lee 2008; Tsytsarau & Palpanas 2012; Medhat, Hassan & Korashy 2014; Pyriani, Madhavi & Singh 2015; Liu 2015; Hemmatian & Sohrabi 2017; Yadollahi, Shahraki & Zaianne 2017; Sun, Luo & Chen 2017). These reviews served as a baseline for choosing the specific methods used in this thesis.

Supervised Machine Learning techniques show relatively better results than unsupervised based or lexicon-based methods in the research. However, unsupervised methods are worthy because the supervised classification of polarity is typically domain-specific and building such a system involves a costly process annotation of a large amount of data for each domain compared to getting new unlabelled data with an increasing number of online communications.

The dictionary-based approach relies on manually-built dictionaries of terms. A significant problem with this approach is that the polarity of many words is context-dependent. Some words have multiple meanings when each meaning can have varying degrees of sentiment. Without the domain context, the approach can hardly assign proper sentiment weight. If there is a sentiment dictionary for one domain, others can adopt it only if it is sufficiently similar to the original (Blitzer et al. 2007). Corpus-based vocabulary decreases weakness of dictionary-based approach by use of computer-stored text containing metalinguistic signs dependent on syntactic patterns in a large corpus, and with a quite high precision incorporating words into different categories (e.g. frequency of occurrence of words in the corpus, parts of speech category) and sentiment classes helping search for words and phrases in the context. Creating own corpus with lexical and statistical methods needs large amounts of labelled training data, but the advantage is a domain-specificity, which cannot be found in standard dictionaries. Much early work in polarity classification was done with restaurant or movie reviews (Turney 2002; Pang, Lee & Vaithyanathan 2002) that had overall scores along with text in the form of scales such as stars. Existing dictionaries like WordNet[16] (Fellbaum 1998) or SentiWordNet[17] (Esuli & Sebastiani 2006) for English are publicly available lexical sources for semantic orientation. In the author's article (Vencovský, Bruckner & Šperková 2016) the lexicon "Sentiment Polarity Dataset Version 2.0" (Pang & Lee 2004) was employed to the model sentiment using Naïve Bayes on the sentence-level. The classifier outputted sentiment as a combination of sentiment polarity and intensity with values from -1 to 1.

Unsupervised clustering methods can achieve high precision for topic classification in datasets with many classes (Pang & Lee 2008). They partly solve the problem of missing important aspects or sentiment indicators in dictionaries as they are not affected by lexical form and consider unknown words and their forms if they occur in the text often enough. The shortcoming is that in the absence of annotated data, it is impossible to identify which feature is relevant for classifying sentiment. Regarding the multiple-meaning, the problem arises with the evaluation algorithms that include only the value that has gained a majority in their calculations (Buryan 2013). Hybrid approaches have therefore been developed. The main advantage of a hybrid approach using a combination of lexical methods and Machine Learning techniques is the ability to get the best of both approaches with high accuracy. These methods then exploit sentiment lexicons, grammatical analysis, and syntactic patterns.

With the higher availability of computing power due to the advances in technology, neural networks experience their renaissance in the last decade in the form of deep learning. Deep learning is the application of neural networks with multiple layers of nonlinear processing units for feature extraction and transformation. The lower layers close to the data input learn simple features, while higher layers learn more complex features derived from lower layer features (Zhang, Wang & Liu 2018). The overview of the different applications of neural networks in sentiment analysis, including emotion mining, contains the study of (Zhang, Wang & Liu 2018).

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[16] Available at https://wordnet.princeton.edu/.
[17] Available at http://sentiwordnet.isti.cnr.it/.

4.5 Aspect Detection Techniques

Mentioned in 2.3, the customers can evaluate and have opinions about many different topics and their aspects, even within one short textual contribution. Although the entire contribution has a particular sentiment, it does not mean that all the words or phrases in the contribution carry the same sentiment. Part of the contribution can be positive or negative or without the subjective opinion of the contributor. Thus, even the overall sentiment of the whole comment is positive; it can also contain negative aspects. The simple Bag-of-Words approaches used in work mentioned above (Turney 2002; Pang, Lee & Vaithyanathan 2002) only look at all the words in the document as unordered basic units ignoring the complex and structural relationships between the words. However, documents are more complicated in the way they express multiple opinions and sentiments. Also, emotional utterances are more complex than simple factual statements. The aspect detection techniques can partly solve the need for finding a context to detect sentiment within the content.

The aim of aspect detection techniques is the extraction of single topics about them the opinion or emotions are then evaluated. The assumption is that the expressed aspects are linked with the expressed sentiment (Liu 2015). Much research in aspect detection is focused on online reviews (Hu & Liu 2004; Titov & McDonald 2008; Mukherjee, Basu & Joshi 2014; Dong et al. 2018). Liu (2012) divides related techniques into four categories mentioned below.

The earliest attempts to detect the aspect were based on classical (I) **information extraction approach using frequently occurring noun phrases** with PoS tagger (Hu & Liu 2004), and then counts their occurrence frequencies using data mining algorithms (Popescu & Etzioni 2007). Such approaches work well in detecting aspects that are strongly associated with a single noun but are less useful when topics include a series of little-occurring terms or abstract terms (Brody & Elhadad 2010). Another approach (II) **exploits syntactic relations**. According to Liu (2015), there are two main types of relations: (1) **Syntactic dependencies depicting opinion and target relations** (Qui et al. 2011) and (2) **lexico-syntactic patterns encoding entity and part/attribute relations.** Researchers also try to solve the issue of ambiguous reviews by refining the (III) **supervised classification** (Pang & Lee 2004; Koppel & Schler 2006; Dasgupta & Ng 2009).

The topic may affect the polarity of sentiment within the same domain. For example, in the domain of restaurants, the adjective “cheap” is positive when discussing food, but negative when talking about the decorations and atmosphere (Brody & Elhadad 2010). Many otherwise neutral terms acquire a sentiment polarity in the context of a specific aspect. The (IV) **topic models** attempt to solve the issue of ambiguity. Topic models treat a document as a set of words, where each word generates a probability distribution over a fixed vocabulary of terms which represent the topic. The most used methods of this approach are lexicon-dependent Latent Semantic Association (LSA) or a statistical lexicon-independent Latent Dirichlet Allocation (LDA) and their various modifications. The overview of 38 existing modifications of LDA methods useful for the detection of Customer Experience elements of satisfaction, emotions and personality systematically reviewed the author in her article (Šperková 2018). Modifications of LDA usually contain joint modelling of both aspects and sentiment words (Blei & McAuliffe 2008; Titov & McDonald 2008; Lin & He 2009; Brody & Elhadad 2010; Dong et al. 2018).

The requirements placed in section 4.2 could be partly fulfilled with an application of the LDA method. The target objects are then understood as latent topics of the documents. The use of LDA over other text analytics methods provides the following benefits:

1) LDA can find topics without prior knowledge.
2) LDA is language-independent.
3) LDA can collect words together that reflect topics of potential interest.
4) LDA analyses data at a highly granular temporal level, it allows for the exploration of dynamics over time.
5) LDA distinguishes the importance of the extracted topics by the intensity of the conversations on each topic.
6) LDA model is not overly restrictive in that it allows each document to be characterised by its own set of topic probabilities.

The simpler LDA models outperform more complex models when there are few reviews. Because the author will perform the analysis based on data from the Czech environment, where customers do not produce much textual data, these models should be satisfying.

In the author's article (Vencovský, Bruckner & Šperková 2016), the Parallel LDA (PLDA) was employed to analyse the reviews in banking domain. The analysis detected seven meaningful topics and authors investigated the number of keywords near every topic. Figure 4.2 depicts the topic-keyword graph based on these topics. The topics were manually labelled after exploration. These labels represent aspect categories according to section 4.1.2. In the next step, Support Vector Machine (SVM) classifier assigned sentiment to each topic with an accuracy of 0.708. The results were presented in interactive dashboards. An example of a dashboard representing the sentiment for single topics in time next to the overall rating of reviews in scale is depicted in Figure 4.3.

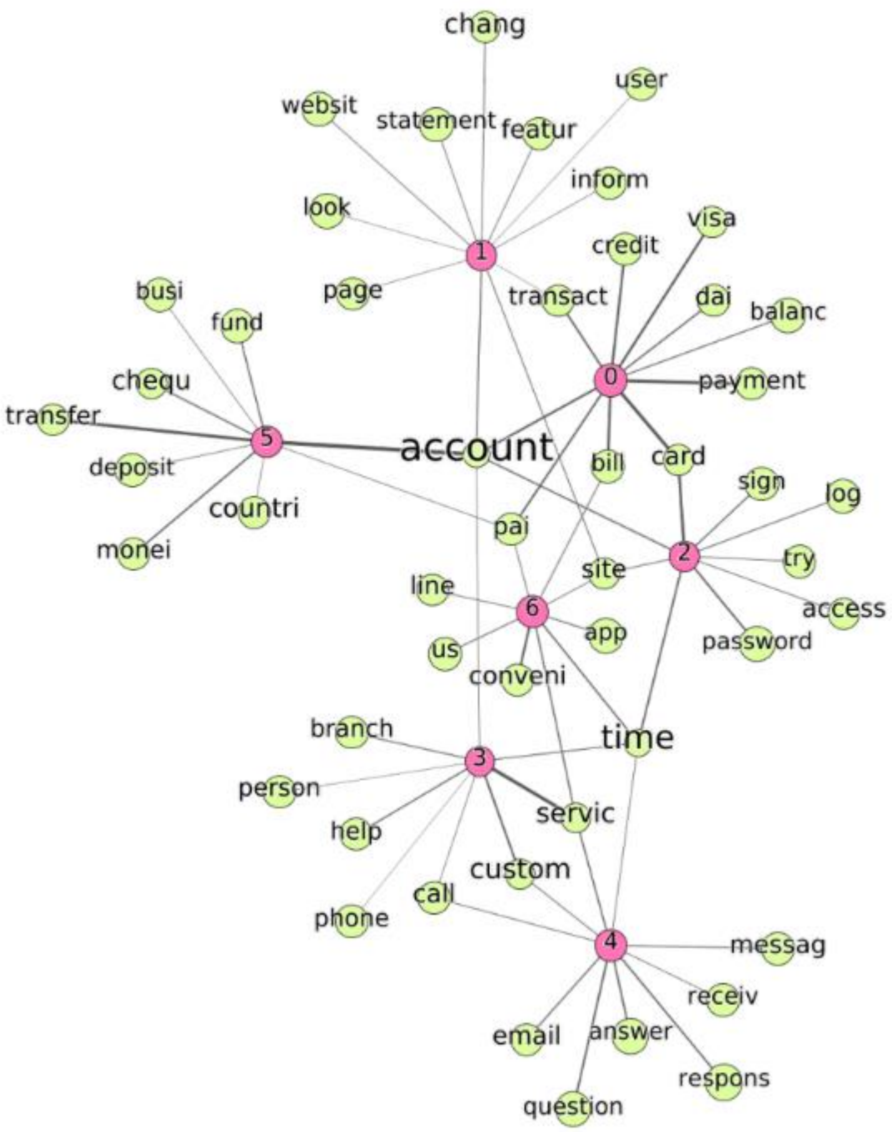

Figure 4.2: Topic-keyword graph modelled based on PLDA (Vencovský, Bruckner & Šperková 2016)

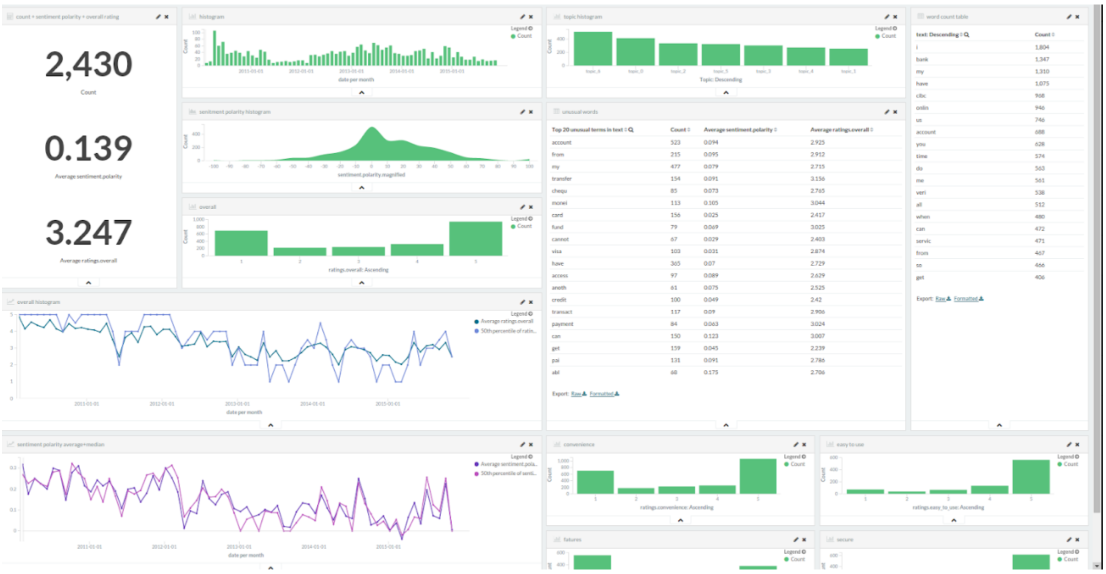

Figure 4.3: Time-period dashboard of topic sentiment (Vencovský, Bruckner & Šperková 2016)

4.6 Emotion Mining and Personality Traits Detection Approaches

Analysing the text for emotions or personality traits detection use similar techniques as an analysis of the sentiment. The main difference is that the detection of emotions and personality traits is a dimensional issue. The concept of emotions and personality were presented in section 2.6. Emotion classification was introduced in section 4.1.

Currently, four approaches dominate the emotion mining: keyword-based (Li, Pang & Guo, 2007), Machine Learning-based (Strapparava & Mihalcea 2008), linguistic rule-based (Shaheen et al. 2014) and hybrid-based approach (Fathy et al. 2017). These methods are well-reviewed in (Fathy et al. 2017; Yadollahi, Shahraki & Zaianne 2017). Almost all the emotion mining studies rely on the use of a lexicon containing the information about the type and strength of the emotion that the word or phrase carries. The most widely cited vocabulary is Pennebaker's Linguistic Inquiry and Word Count (LIWC[18]) (Pennebaker et al. 2015), which is also used in research for personality detection. Another example is the NRC Word-Emotion Association Lexicon[19] (Mohammad & Turney 2010). Next to the association of words with basic eight emotions, the variants of the lexicon also contain sentiment polarity and affect intensity. The lexicon is translated into 105 other languages including Czech.

[18] Available at http://www.liwc.net. Last update in 2015.
[19] Available at http://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm.

Joint topic modelling mentioned in section 4.4 is also used for emotion detection. Emotion Topic Model (ETM) (Bao et al. 2009, 2012) is a joint emotion-topic model adding an intermediate layer into LDA, in which a topic acts as a component of emotion. The Emotion-LDA (Rao et al., 2014a) captures emotions at the topic-level and generates topics without the supervision of emotion labels. Multi-label Supervised Topic Model (MLST) (Rao et al. 2014a) is an extension of the Supervised Topic Model (STM) with supervised LDA (Blei & McAuliffe 2008). The model first generates a set of topics from words and then samples emotions from each topic. Sentiment latent topic model also developed in (Rao et al. 2014b) generates topics directly from emotions. The Affective Topic Model (ATM) (Rao et al. 2014c) generates emotion lexicon (emotion-annotated topics) and predicts emotions to unlabelled documents. The model is intended to predict emotions from a reader's perspective, not the writer's point of view, which is necessary for Customer Experience, but can be used as an emotion lexicon.

Further, Rao et al. (2016) developed the Topic-level Maximum Entropy Model (TME) over short texts. The model generates topic-level features by modelling latent topics, multiple emotion labels, and valence scored by numerous readers jointly. Another joint model is the Emotional Dependency-based Latent Discriminative Model (Quan et al. 2015). This model introduces intermediate hidden variables to model the latent structure of input text corpora with defined joint distribution over emotions and latent variables, conditioned on the observed text documents. Abdul-Mageed and Ungar (2017) built a large dataset for 24 fine-grained emotions extending the (Plutchik 1980) and developed deep learning models based on recurrent neural networks.

Current techniques of personality analysis from textual data are dominated by algorithms that record and track word usage and map the patterns of usage across word categories onto personality traits. The typical methods of extracting personality traits belong to classification (mainly SVM or Naïve Bayes) and regression. The classification methods consider personality recognition as a binary classification problem - whether a user has a personality trait or not (Oberlander & Nowson 2006; Iacobelli et al. 2011; Sumner et al. 2012; Farnadi et al. 2013; Alam, Stepanov & Riccardi 2013). Regression methods estimate the strength of personality traits (Golbeck et al. 2011; Wald et al. 2012). Most of the works construct models based on the closed-vocabulary feature set but use a very small sample of data, which makes the prediction unreliable because of the characteristics of VoC language. Open-vocabularies achieve better performance (Iacobelli et al. 2011; Schwartz et al. 2013) but suffer from a large number of n-gram features. Classical feature reduction methods like PCA ignore the semantic relationships of the n-grams.

The mentioned research considers personality recognition as a single-label classification problem, but customers are considered to have more than just one personality. Liu, Wang and Jiang (2016) treat personality recognition as a multi-label classification problem and use a probabilistic topic model based on LDA technique to predict the personality traits within the framework of Five-Factor Model shown in Figure 2.5. Each topic is characterised by five Gaussian distributions over personality traits as users with different personalities may publish different topics. Model jointly integrates the five personality traits through five mixture Gaussian distributions and predicts the personality strength of the five dimensions simultaneously. Kwantes et al. (2016) also used the Five-Factor Model with LSA performed on a user's short essays and found out promising results for three of five traits.

The Multimodal Joint Sentiment Topic Model (MJST) (Huang et al. 2017) inserts an additional sentiment layer into LDA and takes multimodal data such as emoticon or personality and text into consideration while inferring message sentiment. Joint Author Sentiment Topic Model (JAST) in (Mukherjee, Basu & Joshi 2014) uses LDA to learn the distribution of author-specific topic preferences and emotional attachment to topics. The model uses HMM to capture the short-range syntactic and long-range semantic dependencies in reviews to detect consistency in the author writing style.

4.7 The State of Sentiment Analysis in the Czech Language

The Czech language has a rich syntax, morphology, and high flection that text analytics methods have to cope with it. For example, unlike English, where syntactic negation is easy to detect by the negative particle *not*, Czech uses different ways to express negation (Veselovská 2010). The monography "Sentiment Analysis in Czech" (Veselovská 2017) offers comprehensively established a description of lexical, morphosyntactic, semantic and pragmatic aspects of the Czech language.

Veselovská (2012) presented the initial research on Czech sentiment analysis using Naïve Bayes (NB) and lexicon-based classifier on a small corpus containing polarity categories for 410 news sentences. Sentiment analysis in the Czech language mostly focuses on building polarity classifiers based on supervised Machine Learning techniques on sentence or document-level sentiment. Červenec (2011) performed SVM for polarity classification. Habernal, Ptáček and Steinberger (2015) employed SVM along with a Maximum Entropy (MaxEnt) classifier and compared the influence of different feature settings when performing the classification on a large manually annotated social media dataset. SVM and MaxEnt also performed Ptáček, Habernal and Hong (2014) to detect sarcasm in microblog based on Czech and English data with the cross-linguistic comparison. They also presented a manually annotated corpus of Czech tweets.

Steinberger et al. (2011) presented a multilingual parallel news corpus annotated with opinions towards particular entities, projecting sentiment annotation from one language to the others. In (Steinberger et al. 2012) researchers proposed a semi-automatic triangulation approach to creating sentiment dictionaries in many languages, including Czech.

Habernal Ptáček and Steinberger (2013) introduced three large labelled corpora from Facebook posts[20], movie reviews and product reviews, and evaluated SVM, NB and MaxEnt on these data. The Facebook and movie reviews corpora also served in author's research in Czech banking domain (Šperková & Škola 2015a, 2015b, Šperková, Škola & Bruckner 2015) where MaxEnt classifier was applied. Habernal and Brychcín (2013) employed semi-supervised methods in document-level sentiment analysis of the movie review domain, adding the word cluster features from semantic spaces created on unlabelled external data into standard supervised classification. The classification performance was improved with Gibbs sampling in (Brychcín & Habernal 2013).

The first attempt at aspect-based sentiment analysis in Czech was presented in (Steinberger, Brychcín & Konkol 2014) on an annotated corpus from the restaurant reviews domain. Brychcín, Konkol and Steinberger (2014) extended the system for aspect detection based on supervised Machine Learning for LDA, semantic spaces and sentiment dictionaries. Tamchyna, Fiala and Veselovská (2015) created a corpus from IT product reviews domain[21]. The authors annotated sentences with sentiment and labelled aspect terms, but without any categorisation and sentiment toward the marked targets. In (Hercig et al. 2016), the authors explored several unsupervised methods for word meaning representation. They created word clusters and used them as features for the aspect-based sentiment analysis. Steinberger, Brychcín and Konkol (2014) created an aspect-level corpus freely available[22] to the research community as the first resource in Czech and proposed a baseline system based on supervised Machine Learning. The system is language and domain-independent, thus can be easily trained on data from another domain or language. Konopík, Pražák and Steinberger (2017) introduced a Czech dataset for semantic similarity and semantic relatedness containing almost a thousand

[20] The corpora of (Habernal et al. 2013) with many other Czech corpora are publicly available at websites of the Institute of Formal and Applied Linguistics of Charles University in Prague: https://lindat.mff.cuni.cz/repository/xmlui/.

[21] Available at https://lindat.mff.cuni.cz/repository/xmlui/handle/11234/1-1507.

[22] The corpora for aspect detection based on movie reviews by (Steinberger et al. 2017), same as other mentioned corpora for product reviews, movie reviews and social media domain are available at websites of University of West Bohemia: http://nlp.kiv.zcu.cz/research/sentiment.

of word pairs and their contexts taken from original text corpora including additional examples when the words are ambiguous.

Study of Lenc and Hercig (2016) presents the first attempt at using neural networks for sentiment analysis on Czech data showing promising results. Neural networks also performed Tamchyna and Veselovská (2016) for aspect-category detection as a language-independent approach, but with no significant results in most domains.

Next to corpora created at the University of West Bohemia mentioned above, Czech National Corpus[23] belongs among the publicly available Czech corpora. For syntactic-semantic analysis, the annotated corpus Prague Dependency Treebank[24] (Hajič et al. 2018) is suitable. Corpus contains multilayer annotation, including dependency trees and syntactic functions. The Czech Universal Dependencies 2.3 Model[25] (Straka & Straková 2018) consists of a tokeniser, tagger, lemmatiser and dependency parser. Several syntactic rules for extracting the opinion targets in the Czech language were defined in (Veselovská & Tamchyna 2014). Rules also consider semantic consistency principles typical for Czech like but-clauses, but-coordinations or and-coordinations (Veselovská 2017, p. 55). Also, syntactic dependencies can easier detect negation in Czech.

Czech Subjectivity Lexicon[26] (Veselovská & Bojar 2013) is a list of subjectivity clues for sentiment analysis in Czech containing 4,626 evaluative items together with PoS tags, polarity orientation and source information. For detecting typos, misspellings and other small errors in textual VoC in Czech, the statistical spell-checker Aspell[27] can be performed as it contains the Czech dictionary. The tool Korektor (Richter et al. 2012) offers models for Czech spell-checking and diacritics.

The determination of discrete emotions and personality traits detection from text has not yet been performed in Czech academical research. The author decided to assign emotions according to NRC Word-Emotion Association Lexicon (Mohammad & Turney 2010), which contains terms translated into the Czech language. The first and only academical research in personality detection was published at the end of 2018 (Kučera et al. 2018). The project CPACT (Computational Psycholinguistic Analysis of Czech Text) focuses on the study of the connection between human personality and the words people use, especially on the level of

[23] Available at https://korpus.cz/.
[24] Available at http://ufal.mff.cuni.cz/prague-dependency-treebank.
[25] Available at https://lindat.mff.cuni.cz/repository/xmlui/handle/11234/1-2898.
[26] Available at http://hdl.handle.net/11858/00-097C-0000-0022-FF60-B.
[27] Available at http://aspell.net/.

relations between linguistic characteristics of written and spoken text with outputs of psychological tests aimed at self-assessment of the individual and their assessment by the second person. The results of the study supported the idea that estimating a personality based on a person's language expression in Czech is meaningful. The authors examined personality also in the context of the Big Five model. However, it must be taken into account that the research was created under laboratory conditions where participants write long texts on a given topic, so it is not a spontaneous and natural, short expressions such as VoC.

In this thesis, the personality is detected based on the LIWC vocabulary (Pennebaker et al. 2015). As the LIWC vocabulary is not in Czech, the translation of the text to English is necessary. Qiu et al. (2017) in research examining the relationship between personality and the use of the Chinese language concluded that some aspects of personality estimation based on the language are universal and valid for both English and Chinese speakers, while other aspects are culturally specific. Based on this finding, they recommend an approach to analysis a language based on the analysis of content-bearing words rather than functional words, as functional words are, according to these authors, more sensitive to cultural specificity (Fousková 2019).

4.8 Voice of Customer Integration into Business Intelligence

The aim of this thesis is an integration of the information from textual VoC gained by opinion mining methods into the Customer Experience model, which is a multidimensional data model according to the principles of Business Intelligence. According to Inmon and Nesavich (2007), the essence of text analytics is the ability to analyse the text similarly as the classical Business Intelligence methods analyse numbers in the structured data environment. Some researchers have built frameworks for automatic analysis of single sources of textual VoC data for BI purposes (Liu, Hu & Cheng 2005; Chau & Xu 2012; Peng et al. 2012), however without any context to structured data within the multidimensional data model.

Textual data do not fit the pre-defined data model in relational databases. This fact leads the author of this dissertation to enhance multidimensional database by extraction of useful comments elements (serving as Customer Experience elements) from different data sources, transform and load them into the multidimensional data model in a structured form to enable the further work with the gained information.

The standard approach to storing information from unstructured text creates some semantic repository which serves as a dimension table. Architecturally, the integration of the textual data to the multidimensional models can be completed in two major ways: the first is an extension of traditional OLAP[28] systems with processes to handle documents or with standard BI tools (Ng et al. 2013). The second more data-driven approach which handles specific data needs is presented by textual ETL with the textual data as an input. Park and Song (2012) employ three major text-handling technologies into traditional OLAP systems: (I) *text mining* for extracting keywords, summarizing, classifying or clustering documents; (II) *information retrieval* resulting in documents containing the keywords given as a user query; and (III) *information extraction* to gain structured information according to the schema given by a user with NLP which can be stored in relational database.

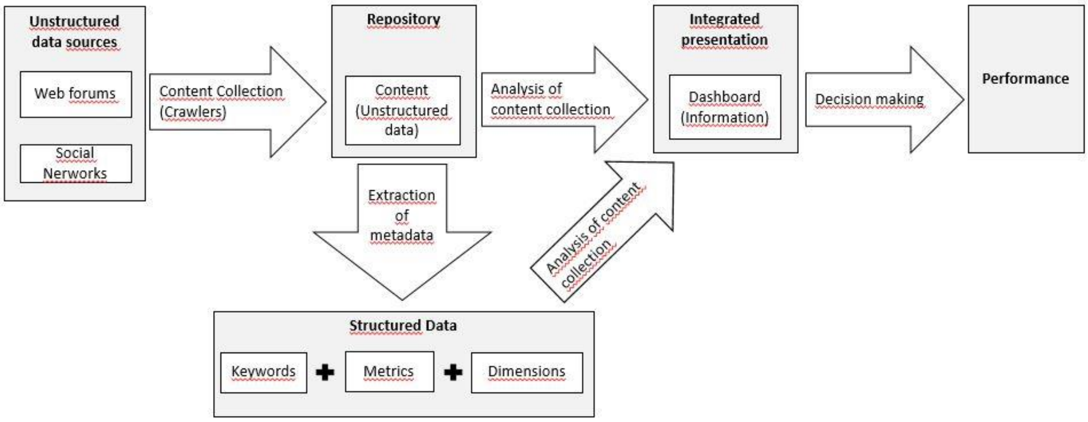

Figure 4.4: Model of the decision-making process from unstructured data (Šperková & Škola 2015a)

Different approaches to the integration of unstructured and structured data offer Baars and Kamper (2008): (I) *Integrated presentation of structured and unstructured content* is performed at presentation layer where structured data as a result of metrics viewed from different dimensions are accompanied with related texts. (II) *Analysis of content collections* focuses on simply extracting metadata (e.g. author, date of creation, length of the comment, addressed product) from collections of unstructured data. The identifiers of the metadata are treated as facts, whereas their fields are used for classification purposes and act as analysis dimensions. This approach allows associate the individual documents with numerical facts directly, based on shared dimensions and to investigate document frequencies, e.g. the number of documents that cover a specific topic and are connected to a particular segment of customers. According to the authors, metadata can be entered manually or extracted with text mining methods. The last most complex (III) *distribution of analysis results and analysis*

[28] OLAP = Online analytical processing. The technology used for multidimensional analysis of a vast amount of data from many perspectives (Chaudhuri & Dayal, 1997).

templates can be imagined as a black-box: it represents pre-configured templates of relevant applications conducted iteratively with calibration and parameterisation. A methodology for the integration of unstructured data into Business Intelligence was designed by (Inmon & Nesavich 2007).

The author's first attempts in the integration of VoC to Business Intelligence were performed in banking domain (Šperková & Škola 2015a, 2015b, Šperková, Škola & Bruckner 2015, Vencovský, Bruckner & Šperková 2016). The main objective of the study of Šperková and Škola (2015a, 2015b) was to create a periodic review of the data evaluating banks according to the context in which their users speak about them on the Internet. The authors developed a model of the decision-making process from unstructured data (Figure 4.4). They collected data from different websites, designed metrics and characteristics to evaluate the bank from the customers' perspective and visualised the gained information in dashboards. Dashboards represent an overview with the sentiment of the talks about the different banks in a specific period and its position within monitored metrics compared to other banks in the market. The example of the Topic Analysis dashboard is depicted in Figure 4.5. The study brought benefits to the field of Competitive Intelligence and customer retention management. The findings provided valuable insight into the business impact of user-generated content in social media - an emerging research area in Business Intelligence.

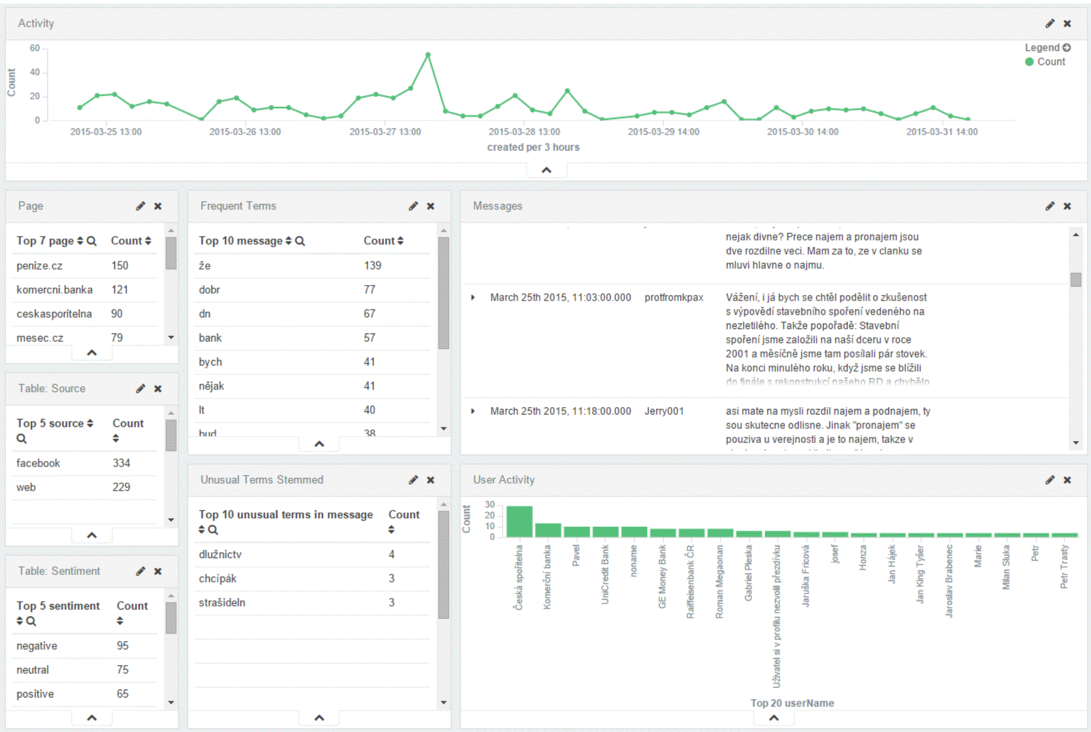

Figure 4.5: The Topic Analysis Dashboard (Šperková & Škola 2015a)

4.9 Methodological Framework for Text Analytics

The process of implementation of text analytics to gain the Customer Experience elements and store them into relational data model can be inspired by the well-known methodology used in data mining, CRISP-DM[29] (Chapman et al. 2000). Since sentiment analysis are based on data mining methods, CRISP-DM is suitable also for opinion and emotion mining tasks. The author suggested the application of the CRISP-DM to the textual data environment in her article (Šperková & Feuerlicht 2017), where authors amplified its phases. CRISP-DM is a reference model, sufficiently generic and transferable, currently practised by companies in many industries in predicting their future business model, especially with customers (Tsiptsis & Chorianopoulos 2010).

CRISP-DM life cycle entails at the highest level of six phases shown in the first row of Figure 4.6: (1) Business Understanding, (2) Data Understanding, (3) Data Preparation, (4) Modelling, (5) Model Evaluation and (6) Deployment. The arrows indicate the most significant and frequent dependencies between the phases. The outcome of each phase determines which phase must be performed next. The sequence of the phases is not rigid. The entire cycle is iterative, moving back and forth between different phases is always required to improve the accuracy of results. A detailed description of the CRISP-DM life cycle can be found in (Chapman et al. 2000).

In (Šperková & Feuerlicht 2017) the authors validated the CRISP-DM with other methodologies – the customer data integration in CRM introduced by (Rainardi 2008) and the unstructured data integration into the Business Intelligence (Inmon & Nesavich 2007) – to ensure its suitability for the Customer Experience model which integrates structured data from CRM as a primary source, and textual VoC. Rainardi (2008) involves five steps in his methodology, including Retrieve, Clean, Store, Update and Distribute. Inmon and Nesavich (2007) suggest necessary steps in setting up and running an iterative process of visualisation or the creation of a relational database full of unstructured data. In Figure 4.6, every row represents a single methodology according to their authors. The colours in columns represent the mapping of their individual phases to the phases of other methodologies.

[29] CRoss-Industry Standard Proces for Data Mining.

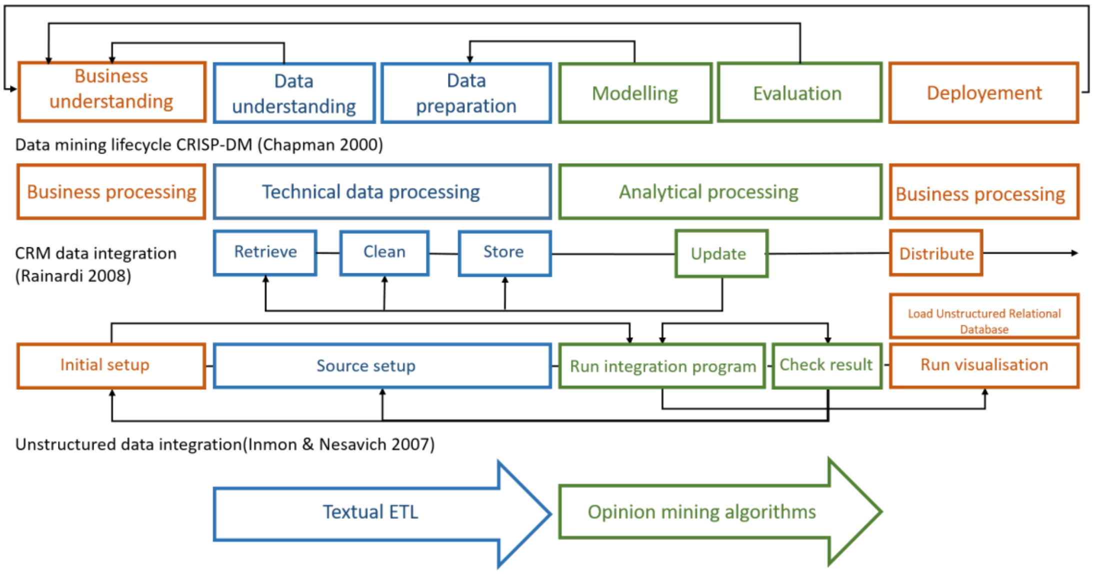

Figure 4.6: CRISP-DM for the integration of VoC to Customer Analytics (Šperková & Feuerlicht 2017)

CRISP-DM serves as a guide for the text analytics application of gaining VoC information to be stored in the Customer Experience data model processed in Chapter 6. Not all the tasks of every phase need to be performed. The execution of the individual tasks depends on the problem being solved. In the author's previous study in the banking domain (Šperková & Škola 2015a), the methodology was used as follow:

1. Identification of the Web pages and social network sites where regular information from customers and users of banking services can be obtained – *business and data understanding*
2. Creating a system that will ensure downloading of the necessary data from the Internet and storing them in the repository – *data preparation*
3. Processing and data analysis – *data preparation and modelling*
4. Design of metrics and characteristics, which evaluate the bank from the customer's point of view – *modelling and evaluation*
5. Design of the dashboard for the visualising the metrics and more detailed information – *evaluation and deployment*

4.10 Chapter Summary

In previous research, much effort has already been inserted into analysing the content of VoC-related textual data without these studies being directly associated with VoC. Many techniques have been developed to achieve the understanding of opinion by the system. However, there is a particular gap between the text analytics of VoC for marketing purposes, and text analytics carried out mainly in the field of computer science, although both areas are dealing with the same data. In articles related directly to the text analysis, the computer scientists aim at specific algorithms for analysing the sample of textual data. They are more concerned with the success of algorithms and their accuracy and effectiveness without a discussion of the application of the results in business.

Although opinion mining algorithms show satisfactory results in research, neither technique can solve all problems. In the Czech environment, the sentiment analysis is not yet well established also due to the complexity of the Slavic language. VoC content is struggling with data quality issues as customers often lack domain expertise and cannot be responsible for the quality of data they contribute. Often, the automated content analysis is restricted in its ability to reveal the communicative intention as the text contains conflicting information, may include many insignificant words, irony and sarcasm, double negations, ambiguous words that have a different meaning in different context, spelling errors, typos, ad-hoc shortcuts, incorrect punctuation, sentence deformed, slang expressions, abbreviations, multiple languages. These deficiencies make it difficult to analyse the content correctly. Buryan (2013) and Veselovská (2017) mention some problems with the content analysis in Czech. The automated data analysis and evaluation must always be followed by an individual assessment of the results by the specialist with the domain knowledge.

The implication of the text analytics results to the marketing and Customer Experience supported by any replicable method describing the process is generally missing. For marketers, practical use is still not fully uncovered. Marketers mostly use separate systems for monitoring of WoM. The VoC should also be mined for unanticipated insights without prespecified hypotheses. There are also missing studies integrating the results with other structured customer data.

The author suggests CRISP-DM methodology as a framework for the execution of text analytics methods in Chapter 6 following the author's article (Šperková & Feuerlicht 2017). This methodology was already successfully used in the author's previous study (Šperková & Škola 2015a, 2015b, Šperková, Škola & Bruckner 2015) in the integration of VoC to BI in the banking domain. For the pertinence and consistency of the application, CRISP-DM was compared to other integration methodologies used in CRM (Rainardi 2008) and unstructured data environment (Inmon & Nesavich 2007) from where the application of CRISP-DM to the

VoC environment overtakes some principles. Figure 4.6 depicts the overlapping of mentioned methodologies.

This chapter complemented the review from Chapter 2 and contributed to the answer of research question *RQ2*: *How to incorporate Voice of Customer and its textual analytics into Customer Experience Measurement to further understand Customer Experience during the customer journey?* The information from VoC is possible to extract and analyse with the methods reviewed in this chapter. In practice, it is usual to combine different methods to gain the required results. This research also combines several methods. Because the author is concerned about the analysis on the aspect-level, the topic modelling approach is performed.

The limitation of this thesis is the Czech language of the input data. The research in Czech is not established at the same level as in English, and only a few methods were performed. The author follows the work of Steinberger, Brychcín and Konkol (2014) regarding the aspect detection and monography of Veselovská (2017) regarding the sentiment analysis. Emotions and personality traits detection has not yet been performed with Czech VoC data, and no lexicons have been created. For that reason, the author uses the NRC Word-Emotion Association Lexicon (Mohammad & Turney 2010), which contains terms translated into the Czech language to assign emotions. The personality is detected based on LIWC vocabulary (Pennebaker et al. 2015).

Chapter 5

Customer Experience Data Model

This chapter represents the development step according to the general methodology of design science research based on Vaishnavi and Kuechler (2015) (see Figure 1.2 on page 19). The outcome of this chapter is the design of the artefact as deliverables *D1* and *D2*.

The *O1* of this dissertation is *to design the Customer Experience multidimensional data model enhanced with storing the information extracted from textual VoC.* According to Business Intelligence, the author understands the Customer Experience data model (deliverable *D1*) as a multidimensional data mart in the data warehouse where all the customer data including the data from textual VoC are stored next to data from other areas of the business. This model directly serves Customer Experience Measurement purposes and contains all necessary data for measuring metrics and determination of Customer Experience elements. The information from textual VoC is gained by text analytics methods and integrated into a structured form with other structured data into the Customer Experience data model. The information from textual VoC is essential for the determination of Customer Experience elements of satisfaction, emotions and personality traits. These elements are imperative for the fulfilment of the objective *O2*: *To enhance Customer Experience Measurement with new elements of customer sentiment, customer emotions and personality traits.*

Based on the integrated data, the metrics for measuring the constituent elements of Customer Experience Measurement are designed (deliverable *D2*). Such a model can approach the unified Customer Experience Measurement essential for Customer Experience management. The chapter contributes to the research question *RQ2: How to incorporate VoC and its textual analytics into Customer Experience Measurement to further understand Customer Experience during the customer journey?* with the fulfilment of the objectives *O1* and *O2*.

The model follows the principles of multidimensionality, according to Inmon (2002), and modelling principles of Kimball et al. (2015). The model is stored in a snowflake schema with the possibility to look at the data from different dimensions. The model representing the logical layer of the BI is aimed to be accessed with a reporting tool available to all the interested stakeholders – analysts, marketers, managers and customer-facing employees. The model aims to facilitate Customer Experience management, its fast deployment in a company, and its impact on other parts of the business.

The model is composed of many entities based on the constituent elements of Customer Experience (see Figure 2.3: Customer Experience construct in section 2.4) — the designed data model reflects these elements in dimension and fact tables. The model, among others, contains typical entities from transactional data which serve metrics calculations based on numeric values (such as behavioural loyalty measured by RFM analysis). VoC extraction aims to capture features related to entities and sentiment/emotions/personality words that represent the orientation of customers on that entity.

5.1 Phases of the Model Design

The author decided to use the reverse process to the data model creation and first to propose the target metrics and indicators to be followed by the companies. Based on the target metrics, the author suggests how to store the underlying data for measurement and reporting these metrics in a data model. The process of the designing of the model is as follows:

1) Design of the Customer Experience Measurement: specification of the metrics and indicators (*D2*).
2) Design of the multidimensional Customer Experience data model: data schema of the tables for the storage of underlying data for the Customer Experience Measurement (*D1*). The design involves the following steps:
    a. Definition of analysis requirements which implicate the specified metrics
    b. Definition of the architectural framework of the solution
    c. Design of the textual stage of the model
    d. Design of the analytical stage of the model

5.2 Justification of the Model and the Starting Points

The artefact design follows and builds on the author's previous research on the integration of VoC into the Business Intelligence in the banking domain (Šperková 2014; Šperková & Škola 2015a, 2015b Šperková, Škola & Bruckner 2015, Vencovský, Bruckner & Šperková 2016).

This section summarises the main points advocating the need and suitability of the Customer Experience multidimensional data model as a building block of the Customer Experience Measurement. The justification results from the literature research in Chapter 2 and the results of qualitative research within the companies in Chapter 3. The section also places the starting points of the model design. The following list represents the main reasons leading to the artefact design:

1) **Set of metrics measuring all aspects of Customer Experience dynamically within the integrated model**

   Research talks about integrated models and approaches to the measurement of the Customer Experience elements (see Chapter 2). The measurement of Customer Experience is currently dependent mostly on the evaluation of single metrics without any context. There is no agreement on robust measurement approaches, and rigorous assessment of metrics that should be collected has been developed to evaluate all aspects of Customer Experience across the customer journey (Lemon & Verhoef 2016; Zaki & Neely 2019). Lemon and Verhoef (2016) emphasise the need for measurement of overall Customer Experience at each stage of the customer journey for every touchpoint, which is still in the early phase in Customer Experience research.

2) **Mitigation of barriers for the full embracement of VoC analysis within Customer Experience**

   There exist many barriers to achieving the full potential of VoC analysis within Customer Experience identified in the qualitative research in Chapter 3 (see section 3.3.3) which can be overcome with the Customer Experience data model (sharing VoC insight across the organisation, struggle to prove financial results, textual VoC is not profoundly analysed, fragmented view of the customer and missing integration of data, missing action with individual customers, missing formalisation of the processes).

3) **CRM data are not sufficient for the Customer Experience Measurement**

   CRM systems exist separately from all the existing solutions about textual VoC, which lead to organisations incorporating text analytics into their customer relationship management programs outside the CRM solutions (Reamy 2016). Although companies typically possess much quantitative CRM data on customer buying habits and classifications, there is little knowledge about the emotions of these customers and their evaluations. Customer Experience is more complicated than simple CRM metrics alone (Zaki & Neely 2019). Information like opinions, emotions, but also personality, which cannot be found in transactional and other structured data, are partly hidden in customers' written expressions.

   The model exploits data from the analytical CRM, but not to serve as a complex platform based on CRM but as a self-contained expandable and transferable data model containing the data from textual VoC among other data, which can be implemented in any Business Intelligence solution.

4) **A unified, consolidated place for all data from various sources and touchpoints**

Since the underlying data for Customer Experience Measurement are located in different internal and external sources of the company, the examination of VoC for managing Customer Experience from one source only is incomplete. Companies should collect both qualitative and quantitative data from these sources to acquire a holistic view of Customer Experience. When accessing data from separate systems, stakeholders are not able to interconnect the data according to their identifiers or metadata and find valuable information about individual customers resulting from various customer data and VoC interconnections. Designing reports for comprehensive Customer Experience Measurement based on perceptual and behavioural metrics, stakeholders need to access data from one integrated physical place stored in a unified form. The unified storage ensures the accuracy and reliability of the following measurement with the less human effort.

5) **Part of value creation chain in Customer Experience Management**

Customer Experience Management emphasises value creation. From a managerial perspective, the results from the literature review in Chapter 2 suggest that firms should pay attention to textual content when managing Customer Experience and, more importantly, focus on the right measures. The value cannot be calculated merely from structured data as it is impossible to set the probability of a rise of such surprising information from VoC. Successful Customer Experience management needs to systematically collect VoC, mine that VoC for insights, share the insights with the business, and incorporate the insights into business decisions. That requires the ability to design, implement, and manage Customer Experience in a disciplined manner. As is seen from the results of qualitative research in Chapter 3, the most challenging for marketers is the synthesis of information from VoC into useful reports. The model particularly targets this synthesis of the information to gain new insight into the Customer Experience.

6) **Customer perspective**

Most research analyses the sentiment and therefore satisfaction only from the product/service/organisation perspective (Vencovský 2018; Farhadloo et al. 2016) where the sentiment is aggregated for single products or product features, but it is not possible to map the sentiment back to the customer who wrote the comment.

Customer perspective is neglected. When appraising an interaction, it is essential to evaluate the polarity of the interactions in a particular context – not only from the viewpoint of a marketing objective but also customer perspective – if the company wants to contribute to customer retention.

Yaakub (et al. 2012, 2015) proposed an enhancement to the customer analysis multidimensional data model for the ontology model to calculate and analyse the opinion orientation of some groups of customers for products in certain levels based on the ontology gained from textual customer reviews.

The designed data model of Yaakub (2015) represents the starting point for the data model design in this thesis. Yaakub's research is missing integration with other structured customer data on an individual level, so the designed model stands alone without any context to other tables from the customer dimension. However, Yaakub emphasises the importance of the integration of the opinion from textual data to other customer structured data. This thesis addresses the shortage of Yaakub's ontology narrowed only to five products. It also extends the opinion fact table by emotions and personality traits linked to the customer dimension, as described in section 4.2. The Customer Experience data model significantly expands on Yaakub's model by adding other tables with textual information and references to tables with the structured data from other sources. The Customer Experience data model results from the needs of Customer Experience Measurement. The artefact of Customer Experience Measurement primarily builds on and extends the research in Customer Experience conducted by Lemon and Verhoef (2016) and Zaki and Neely (2019).

5.3 Design of Customer Experience Measurement

Measurement in Customer Experience lacks clear definitions of the constructs and dimensionalities (see Chapter 2). The research emphasises the need for the development of robust metrics for the Customer Experience Measurement (Verhoef et al. 2009; Jain, Aagja & Bagdare 2017; Lemon & Verhoef 2016; Zaki & Neely 2019). In this section, the author proposes the metrics and indicators for measuring Customer Experience.

The proposal of the metrics represents the application of the Customer Experience construct with its constituent elements designed in Figure 2.3 in section 2.4 (deliverable *D1a*) as the result of a thorough analysis of the current research in Customer Experience described in Chapter 2. The selection of the specific metrics (Table 5.1) and corresponding dimensions (Table 5.2) follows the literature review in Chapter 2 and the results of the quantitative research in Chapter 3. During the interviews, the author asked the participants what metrics and indicators are important for the monitoring and evaluating the Customer Experience in their organisations. The measurement is enriched with *new elements of customer sentiment, customer emotions and personality traits* according to the objective *O2.* According to the research (see section 2.6), these elements are latent constructs of the Customer Experience, which need to be involved in Customer Experience Measurement.

Since Customer Experience is in this thesis assumed as a customer perspective during their decision journey, the author suggests measuring the following metrics evaluating elements of Customer Experience from a customer perspective during the customer journey. The metrics evaluating the Customer Experience from the company perspective are neglected as the goal is to get to the individual level of the customer. Metrics summarise various aspects of the data in the multi-level aggregate form and are comparable to the surveyed dimensions according to constructs reviewed in Chapter 2.

The metric is in this thesis understood as a quantitative or qualitative indicator or an evaluation criterion to assess the level of Customer Experience with its constituent elements. The primary purpose is to highlight the relevant facts that the company needs to address to improve the level of Customer Experience. The underlying data for the evaluation of the metrics are stored in the data model, which is designed for the querying in order to gain the metrics results. The metrics should reflect the design requirements in section 5.2.

The metrics are supposed to be visualised in reports and dashboards - applications that organise metrics in a clear and intuitive graphical form (Pour et al. 2012) for further managing Customer Experience. The metrics listed in Table 5.1 are designed on a general level as they can be customised according to the business and available data. The table contains the definition and construction of metrics, the source of data for the metrics, and related Customer Experience elements ensuring the placing of the metrics into the construct.

Table 5.1: Metrics and Indicators in Customer Experience Measurement

Metric/Indicator	Definition/Construction/Sub-metrics	Related CX elements	Source of data
Customer Effort Score (CES)	Determines how much effort a customer has to exert to get a result (issue solved, request fulfilled, product purchased, question answered) on a scale from very easy to very difficult.	Engagement (cognitive) Satisfaction Personality	Structured operational data
Customer Satisfaction Score	Determines satisfaction on a scale from very unsatisfied to very satisfied.	Engagement (affective - intimacy) Satisfaction (evaluative)	Structured questionnaire
Discrete Emotion	Detects customer's primary emotions according to the model of (Plutchik 1980): Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, Trust. More emotions from Plutchik's Wheel of Emotions can be added.	Emotions Satisfaction Loyalty (attitudinal)	Textual VoC
Emotional Value	Detects the emotional value based on detected emotions on the scale: strongly negative, negative, rational, positive, strongly positive.	Emotions	Textual VoC
First Response Time	Calculates the average amount of time elapsed until initial response to the customer's contact according to the type of the contribution: comment type = complaint, suggestion, requirement	Satisfaction	Operational CRM (structured)
Involvement level	Indicates the involvement level based on the following metrics: - Number of unique site visits - Number of advertising impressions and clicks - Number of website page views - Time spent per session - Time spent per page - Number of in-store visits - Number of newsletter subscriptions	Engagement	Structured web analytics data

Metric/Indicator	Definition/Construction/Sub-metrics	Related CX elements	Source of data
Net Promoter Score (NPS)	Determines detractors, promoters and passive customers. The indicator represents the answer to the question "How likely you would recommend company/product/service to a friend or colleague?" on a scale from 0 = very unlikely to 10 = very likely) - detractors, for a score of 0–6, - passives, for a score of 7 or 8, - promoters, for a score of 9 or 10.	Satisfaction (evaluative)	Structured questionnaire
Number of cancellations	Indicates the number of cancellations the customer made (i.e. cancel an ordered service, opt-out).	Satisfaction	Structured transactional data
Number of complaints	Indicates the number of complaints the customer sent to the company by a summary of individual comments with the type = complaint.	Engagement (cognitive - interaction) Emotions Satisfaction	Textual VoC
Number of compliments	Indicates the number of compliments the customer sent to the company by a summary of individual comments with the type = compliments.	Engagement (cognitive - interaction) Emotions Satisfaction	Textual VoC
Number of public comments	Indicates the number of public contributions (WoM) by summary.	Engagement (affective - interaction) Loyalty (attitudinal)	Textual VoC
Number of requirements	Indicates the number of suggestions the customer sent to the company by a summary of individual comments with the type = requirement.	Customer expectation Engagement (cognitive - interaction) Emotions	Textual VoC

Metric/Indicator	Definition/Construction/Sub-metrics	Related CX elements	Source of data
Number of returns	Indicates the number of returns the customer made (money back).	Satisfaction	Structured transactional data
Number of suggestions	Indicates the number of suggestions the customer sent to the company by a summary of individual comments with the type = suggestion.	Engagement (cognitive - interaction) Emotions	Textual VoC
Personality	A mixture of personalities values according to the Five-Factor model (McCrae & John 1992). Can be visualised as a radar graph. - Openness - Agreeableness - Conscientiousness - Extraversion - Neuroticism	Personality	Textual VoC
Problem Resolution Time	Calculates the average amount of time for resolution of the customer's complaint: between when the customer first creates an issue ticket to when the issue is solved.	Satisfaction	Operational CRM (structured)
Recency, Frequency, Monetary (RFM)	Determines - Recency – How recently made the customer purchase (interval between the time of the last transaction and first day of each season) - Frequency – How often the customer purchases (number of days which occur a transaction during each season - Monetary – How much the customer spent (the average amount of money spent on purchases during each season) The result is the customer's placement in the cube according to binning the scores of frequency, recency and monetary into five equal frequency bins (Kohavi & Parekh 2004).	State in the Customer Journey Engagement (interaction) Loyalty (behavioural)	Structured transactional data

Metric/Indicator	Definition/Construction/Sub-metrics	Related CX elements	Source of data
Referral Value	Indicates the customer referral value by the following metrics: - Reach: Number of impressions/responses/shares (forwarded content) to the customer's contributions - Sentiment of the responses to the customer's contributions - Importance of the responded contacts to the customer's contribution - Number of sent invitations to join the community by customer - Number of public contributions (WoM) - Sentiment of the shared contributions (WoM sentiment)	Sentiment Engagement (affective - influence)	Textual VoC Structured web analytics data
Review Score	Indicates the quality of the subject of consumption at a numerical scale.	Satisfaction (evaluative)	Structured VoC data
Sentiment	Calculates the sentiment of the customer contribution as a value to determine the polarity of the sentiment: - positive, if sentiment value > 0, - negative, if sentiment value < 0, - neutral, if sentiment value = 0.	Satisfaction (emotional) Loyalty (attitudinal) Engagement (affective - intimacy)	Textual VoC
Share-of-Wallet	Determines how much of available budget customer spent at the company versus competitors. Customer's total revenue/total spend x 100	Engagement Loyalty (behavioural)	Structured transactional/demographical data
Value of Knowledge	Indicator of demanding (high value) and difficult customers (low value) - Demanding: willing to participate in finding problem solutions - Difficult: requires energy on solving issues without the support of knowledge	Engagement	Structured operational data Textual VoC

In reports, metrics can be viewed from many dimensions, for immediate use in decision-making processes in the organisation. The examples of considered dimensions for filtering, slicing and drilling the metrics are defined in Table 5.2. The results of metrics (Table 5.1) can also act as dimensions to filter/slice/drill other metrics. For example, customer satisfaction is determined by customer *sentiment*. Customer sentiment can be assigned both to all of the customer's comments as a summary sentiment and to a specific comment, object or aspect only. Further, sentiment can be used to slice the measurement of *most active customers* (determined by a number of comments posted by the customer) and show only those with negative sentiment polarity. All metrics are related to the time dimension, and customer dimension as the measurement is aiming to the customer perspective.

Table 5.2: Dimensions in Customer Experience Measurement[30]

Examples of dimensions resulting from the data model	**Description**
Channel dimension	Stores the different touchpoints for interacting with customers. Represents the source of data of VoC (e.g. review, email, post on a social network)
Customer dimension	Stores information (mainly demographic) about the customer
Object dimension	Represents the product, service, topic, issue, person or event represented as an object detected in the text
Aspect dimension	Represents the aspects of the object (dimension of quality, functionality, component) detected in the text
Comment dimension	Detect type of the comment (complaint, compliment, suggestion, requirement, need)
Time dimension	Universal periods used throughout the model (year, quarter, month, week, date, datetime)
Sentiment polarity	Detect the polarity of the sentiment - *Positive* - *Negative* - *Neutral*
Loyalty segment	Determines customer loyalty based on a two-dimensional model of (Dick and Basu 1994). The result is the customer's placement in the matrix. - *No loyalty* (low repeat purchases, weak relative attitude) - *Spurious loyalty* (high repeat purchases, weak relative attitude) - *Latent loyalty* (low repeat purchases, strong relative attitude) - *Loyalty* (high repeat purchases, strong relative attitude)
Recency, Frequency, Monetary (RFM) segment	Determines the RFM segment based on the measured RFM score. The segments can be refined according to stakeholders' needs.

[30] The values in dimensions (e.g. particular segments) can change according to the stakeholders‘ needs.

Examples of dimensions resulting from the data model	Description
	- *Loyal customer* (highest recency, highest frequency, highest monetary) - *Potential loyal* (high recency, high monetary, more than one purchase) - *New customer* (high recency, low frequency) - *Attention seeker* (high monetary, high frequency, low recency) - *Sleeping customer* (lower recency, lower frequency, lower monetary) - *Lost customer* (lowest recency, lowest frequency, lowest monetary)
Customer state in the journey	Dimension extends the RFM result for other information gained about the customer. Detects the customer state in his customer journey according to (Buttle & Maklan 2015): - *Suspect*: potential customer fit the target market - *Prospect*: the customer fits the target market profile and is being approached for the first time - *First-time customer*: the customer makes the first purchase - *Repeat customer*: the customer makes an additional purchase. - *Majority customer*: the customer selects the company as a supplier of choice. - *Loyal customer*: the customer is resistant to switching suppliers and has a strong positive attitude to the company or offer. - *Recovered customer* (customer who was considered as lost in last defined period, but made a purchase in the current period)

The classification to the segments which can serve further as views to some metrics as dimensions can depend on results of other metrics. For example, the classification into loyalty segment depends on the results of the RFM score and engagement level (spreading positive WoM). The RFM score ascertains if the customer is still alive and makes purchases, but it may be that customer has not purchased for an extended period, but still talks positively about the company, thus spreading positive WoM. Such a customer would be in the loyalty matrix more in the left top corner as a latent loyal. The understanding of the causes of weak and negative attitudes in a customer can help companies identify barriers to purchase.

The definition of the segments and the borderlines between the segments depends on the business case and the goals of the company. The right segments should fulfil characteristics of similarity within the segments, differences between the segments, sufficient size of the segment and verifiability over time.

5.4 Analysis Requirements for the Customer Experience Data Model

The first step to designing the data model for Customer Experience is an identification of different types of categories of analyses that are relevant to Customer Experience, which implicates metrics evaluation listed in Table 5.1. Specific data points of interest are identified from both literature review in Chapter 2 and qualitative research in Chapter 3. Data maintenance issues also must be considered to ensure data history, integration, and expansion of the model with new data sources. The Table identifies the minimum analysis requirements for the design of Customer Experience data model. These requirements follow the Customer Experience construct (Figure 2.3) designed in section 2.4. There is no significance to the order of listed requirements in the table. The fulfilment of the requirements in the real-world environment of e-commerce is validated further in Chapter 6.

Table 5.3: Minimal analysis requirements for the Customer Experience data model

Analysis Requirement	**Description**
Campaign analysis	Ability to evaluate the effectivity of the campaigns through different channels according to customer responses on them.
Customer behaviour	Ability to analyse customer behaviour through different channels.
Customer expectations and perceptions	Ability to distinguish between customer expectations and perceptions in the textual comments and their type.
Customer loyalty	Ability to understand loyalty patterns among different relationship groups and to evaluate the level of customer loyalty.
Customer personality and emotions	Ability to determine customer emotions and personality.
Customer profitability	Ability to determine the profitability of each customer.
Customer retention and attrition	Ability to track customer retention and identify the root causes of attrition.
Customer satisfaction	Ability to asses customer satisfaction with sentiment detection.
Customer scoring and segmentation	Ability to score and segment customers into multiple segments.
Customer state in the journey	Ability to determine the customer state in the decision journey.
Opinion target analysis	Ability to determine target objects and their aspects in the customer comments.
Product/service experience analysis	Ability to determine the product/service experience from the customer perspective, including the returns, delivery performance, time to solve complaints.
Trend analysis	Ability to perform trend analysis.
Data Maintenance	Ability to maintain integration of data from various sources, history, efficiently update data.

5.5 Architectural Framework

The approach to the integration of textual VoC in this thesis applies textual ETL onto the documents and extracts information as values of the entities and their attributes founded in the text. Information is stored in the multidimensional model as structured data. In (Park & Song 2012), relational OLAP and textual OLAP exist independently and are consolidated in another OLAP module in "total BI platform". As the information technology has evolved over the last few years as well as the ability of relational databases to store large volumes of data and their processing speed, there is no necessity for two separate multidimensional databases. Thus, the author stores both the inherently structured data and information from textual data into one multidimensional database.

However, the process of integration enquires more stages for the transformation of the data. Therefore, the author suggests three stages as depicted in Figure 5.1: textual pre-stage for storage the textual data pre-processing results which serves as a data layer for further analytical methods, textual stage for storage of information gained by text analytics methods above the content and analytical stage linked to the textual stage for the calculation of Customer Experience metrics as a logic layer of the BI. The analytical stage stores the structured customers' data with the results of analytical processes (such as data mining models) where Customer Experience elements are modelled based on the extracted information from textual data. The textual stage must be loaded first to fill tables in the analytical stage. The loading phase into the model is a part of textual ETL.

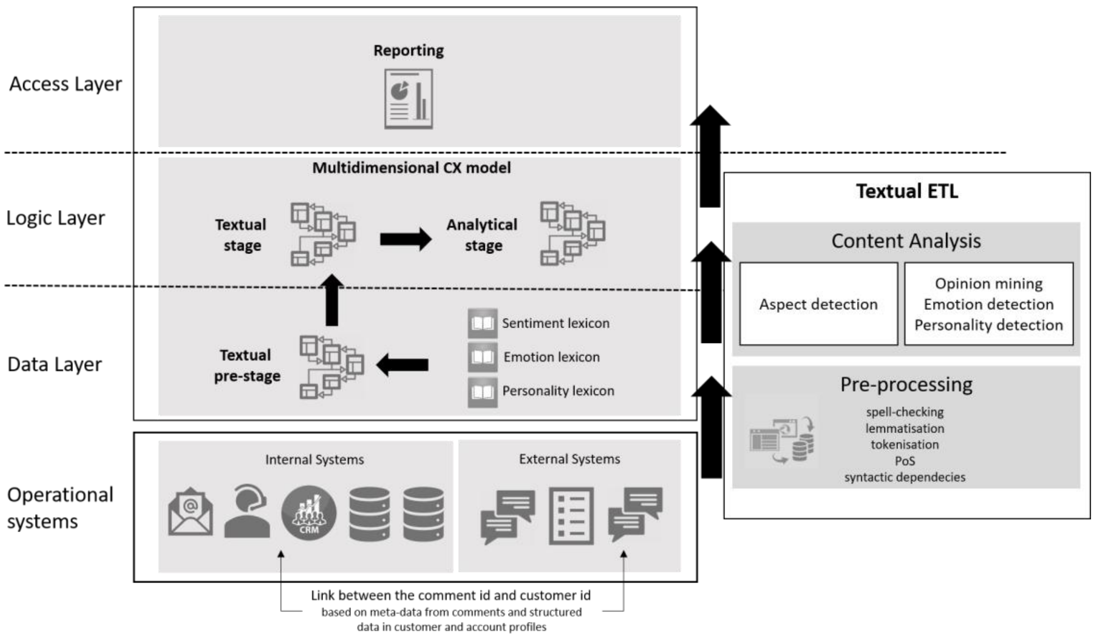

Figure 5.1: BI framework for the process of VoC integration to Customer Experience

Figure 5.1 shows the integration process of textual VoC to the Customer Experience Measurement from the data source collection to the reporting. The pre-processing phase includes data cleaning and feature extraction and selection (see section 4.2). Based on the pre-processed data, the content analysis is performed, and its results are then loaded into the textual stage. Based on the information from the textual stage, the analytical stage is further modelled.

5.6 Textual Stage

The textual stage is the result of the textual ETL and can be divided into the pre-processing phase and content analysis where the models are deployed (see Figure 5.5). The results of pre-processing can be stored in a textual pre-stage. In a pre-stage, the lexicons are stored for applications of models for content analysis or other data suitable for further processing. Among these lexicons belong sentiment, emotion and personality lexicons for detection of these elements, but also domain ontologies for aspects and objects for results refinement.

The results of text analytics are stored in the textual stage – sentiment, emotion, personality traits and opinion targets (objects and aspects) which further serve for measurement of Customer Experience elements in the analytical stage.

5.6.1 Input data

The customer interacts with the company and its other customers or prospects through different channels. The example of the process of collection of initial data from two different sources through web crawling and application interface is described in the author's article (Šperková, Škola & Bruckner 2015) and not further discussed in detail in this thesis. The data are transferred in a clearly defined format suitable for storage in the relational database. The input to the ETL process for Customer Experience model is a structured table with all the raw interactions containing the opinions of the customers which represent opinion holders. Every single interaction is stored in the database under its identifier. The meta-data of one interaction represents one row in the table, including a raw text of the content. The input table contains at least these attributes:

- *Interaction identifier*: the unique identification of the interaction
- *Contributor identifier*: the unique identification of the user who expresses the comment
- *Source identifier*: the unique identifier of the source of the interaction
- *Timestamp*: the exact time the comment was sent or posted
- *Comment text*: the content of the interaction in plain text

Other attributes can be added (if any exist) containing additional information, for example, other contributor's identifiers, if the comment is accompanied with the rating in Likert-type scale or if the comments belong to different dimensions of experience.

The table stores the raw textual data before any text analytics process, so it is always possible to return to the original text. Every comment discusses at least one target object (opinion target) and not all the target objects discussed in one comment must be correlated. In the textual stage, this table represents the table *Comment* in the model and can be completed by other transformed input data from different channels. The determination of the opinion target is a task for text analytics (see section 4.2).

5.6.2 Pre-processing Phase

The pre-processing of the textual comments is based on standard features extraction and selection processes described in section 4.2. The comments are spell-checked and parsed to sentences based on punctuation, tokenised and lemmatised. After tokenisation, the morphological tags (attribute *Tag*) are assigned to the words and store to the relational table *Entity* (Table 5.4). The morphological tags[31] carry information about Parts of Speech (PoS) or negations which are extracted to the own columns (*PoS_Tag* and *Negation*) as this information is used later in the analysis.

To encompass entire phrases or n-grams in the text as subjects of mining methods (for example an aspect *wellness weekend* in dependency tree in Figure 5.2) and not only features represented by frequent nouns, adjectives and adverbs; the syntactic dependencies depicting opinion and target relations are also assigned[32] and stored in column *Dependency_Relation*. The PoS with dependencies can be visualised as grammatical trees (see Figure 5.2), for example, with the help of graph databases. Querying the graph database with the specified rules[33] enables to complete the objects and aspects.

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[31] The morphological tags are results of the morphological analysis which works with isolated verbal forms, regardless of their context. Each tag is a string of 16 characters, in Czech Universal Dependencies 2.3. Model for UDpipe (Straka & Straková 2018) available at https://lindat.mff.cuni.cz/repository/xmlui/handle/11234/1-2898 used in this thesis, the 15th position is missing. Every position has its meaning (see https://wiki.korpus.cz/doku.php/seznamy:tagy#morfologicke_znacky_tagy in Czech). The first position determines PoS (N for the noun, V for the verb, A for adjective etc.), the second position contains the detailed determination of the word part. At the 11th position is determination of negation.

[32] For the Czech language is usable Czech Universal Dependencies 2.3. Model for UDpipe (Straka & Straková 2018) based solely on Universal Dependencies 2.3 treebanks.

[33] See section 6.2.4 in Chapter 6 for a specification.

Figure 5.2 shows the syntactic dependencies of two sentences based on a Czech review dataset[34] from the case study conducted in Chapter 6. The grammatical trees were generated with the use of application UDpipe[35] (Straka & Straková 2017). The relational storage of the values gained by pre-processing of these two sentences is depicted in Table 5.4.

Table 5.4: Relational table with pre-processing results[36]

Comment_Id	Sentence_Id	Token_Id	Token	Lemma	Tag	PoS_Tag	Dependency _Relation	Negation
2567	1	1	Tento	tento	PDYS1----------	DET	det	
2567	1	2	zážitek	zážitek	NNIS1-----A----	NOUN	nsubj	
2567	1	3	by	být	Vc-------------	AUX	aux	
2567	1	4	se	se	P7-X4----------	PRON	expl:pv	
2567	1	5	opravdu	opravdu	Db-------------	ADV	advmod	
2567	1	6	neměl	mít	VpYS---XR-NA---	VERB	root	neg
2567	1	7	tvářit	tvářit	Vf--------A----	VERB	xcomp	
2567	1	8	jako	jako	J,-------------	SCONJ	mark	
2567	1	9	wellness	wellness	AAXXX----1A----	ADJ	amod	
2567	1	10	víkend	víkend	NNIS1-----A----	NOUN	advcl	
2567	1	11	.	.	Z:-------------	PUNCT	punct	
2899	4	1	Létání	létání	NNNS1-----A----	NOUN	nsubj	
2899	4	2	by	být	Vc-------------	AUX	aux	
2899	4	3	mohlo	moci	VpNS---XR-AA---	VERB	root	
2899	4	4	být	být	Vf--------A----	AUX	cop	
2899	4	5	levnější	levný	AANS1----2A----	ADJ	xcomp	
2899	4	6	.	.	Z:-------------	PUNCT	punct	

The pre-processing phase of the textual data serves directly for the text analytics methods, and it is not critical to store the intermediate results to the database. Nevertheless, these results can serve for further improvement and adjustment of the methods or as a domain knowledge corpus which can be enhanced with other attributes, for example, entity type (number, person, organisation and similar) or even sentiment. Such results can be stored in a relational table, which has a relation to the transformed input table *Comment*, as demonstrated in Figure 5.3.

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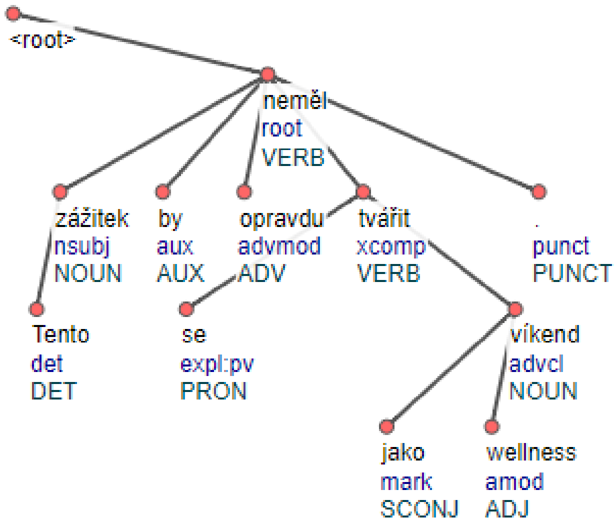
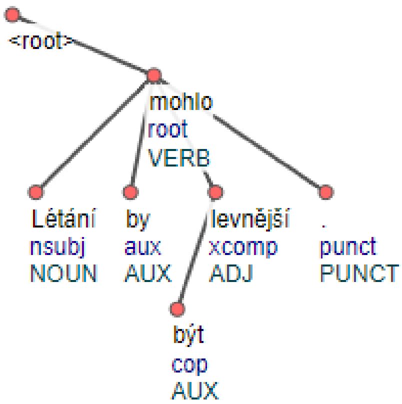
[34] The English translation of the sentence is in quotation marks.
[35] Universal Dependencies Pipeline available at http://lindat.mff.cuni.cz/services/udpipe/
[36] The grammatical annotation is in relation with universal dependencies framework in https://universaldependencies.org/cs/: det = determiner, nsubj = nominal subject, aux = auxiliary, expl:py = relation between the verb and the clitic, amod = adjectival modifier, advmod = adverbial modification, xcomp = infinitival complement, cop = copula, punct = punctuation, advcl = adverbial clause modifier.

One comment contains many tokenised entities for the recognition of opinion targets and appraisal words in the next steps.



Tento zážitek by se opravdu neměl tvářit jako wellness víkend.

(This experience really did not look like a wellness weekend.)



Létání by mohlo být levnější.

(Flying could be cheaper.)

Figure 5.2: Dependency tree for evaluative sentences generated with UDPipe

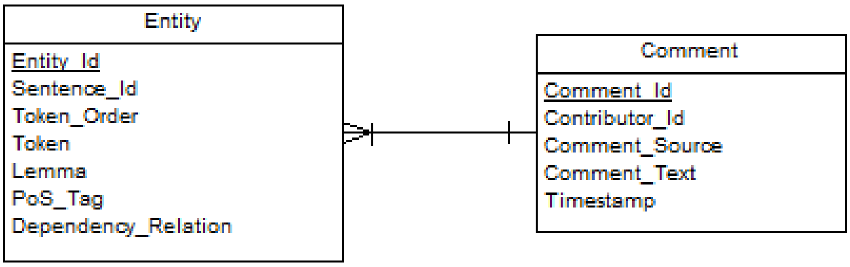


Figure 5.3: Relationship between tables Comment and Entity

Only the opinion targets (as objects and aspects) enter the next phase. Features and other words or phrases – which are representative words of aspects or appraisal words – do not enter the model. They serve only as evaluative words for the modelling of sentiment, emotions or personality traits. The aspect extraction is already a result of content analysis after pre-processing.

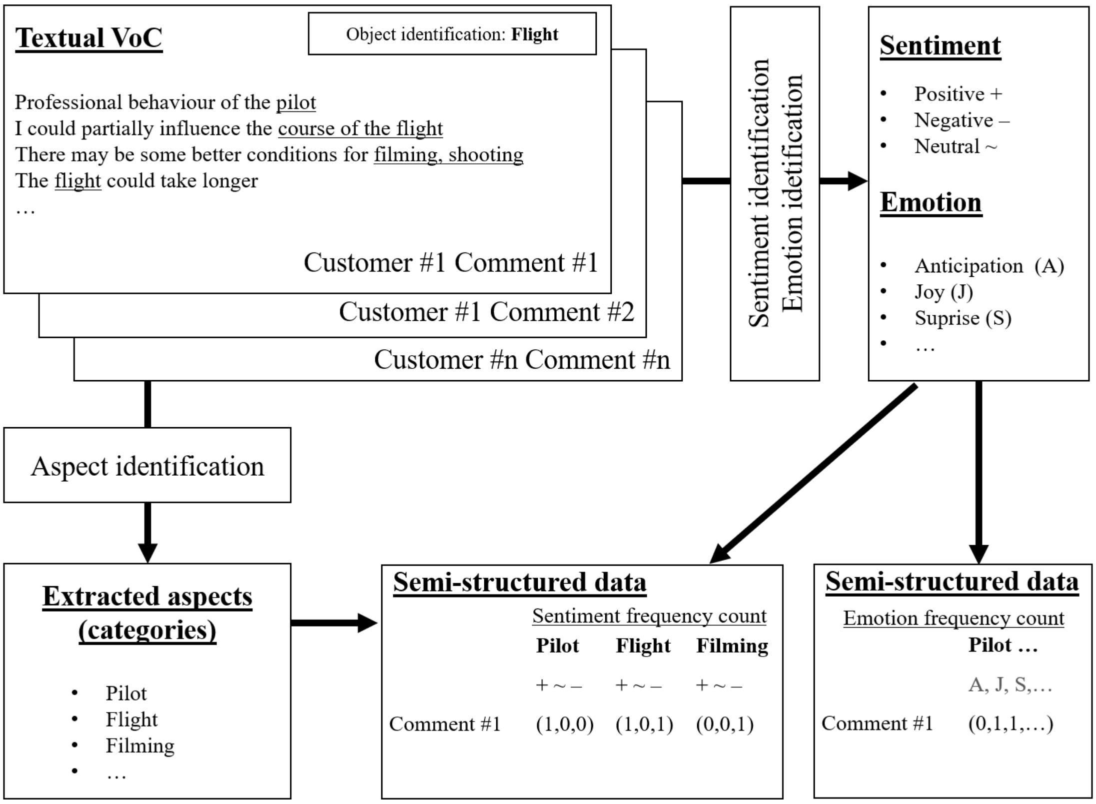


Figure 5.4: The process of transforming textual VoC into semi-structured data

The transformation of the raw input text is processed through semi-structuralisation similarly to Farhadloo et al. (2016), but with the preservation of customer dimension, that means without aggregation to a product perspective. The input text is transformed to semi-structured data (see Figure 5.4) of semantic elements which can be loaded into the multidimensional database. The aspect detection with text analytics methods is complemented by domain knowledge predefinition (for example, with the help of mentioned syntactic dependencies). This approach is also suggested by Yaakub (2015).

5.6.3 Conceptual Data Model of Textual Stage

The textual stage represents the entities capturing the tacit knowledge available in textual comments. Figure 5.5 depicts the underlying conceptual model[37] proposed to capture

[37] The schema is designed with the modelling tool PowerDesigner 12.

customers' opinions. The model shows only the necessary attributes for storing the textual data. The relation to ontology tables (emotion/personality/sentiment lexicons) and history tables is not depicted due to the readability of the model. For simplification, the author adheres only to concepts related to ***object*** and ***aspect*** as she considers them to be sufficient for the model's needs.

The model builds on the knowledge of Yaakub (2015) and extends it for the purpose of this dissertation. The issue of Yaakub's model for opinion is that based on the primary key, the fact table can store only one feature (in this thesis understood as aspect) per comment, even though he wants to gain sentiment for the whole feature hierarchy. This shortcoming is rectified in this thesis by adding the fact table *Opinion* into the conceptual model.

In contrast to Yaakub's multidimensional model, the Customer Experience model needs to relate satisfaction and sentiment to relevant customers. Therefore, it is not sufficient to retain the sentiment value only for the particular aspect in the *Aspect* table, but it is needed to determine which customer holds this opinion as opinions differ customer from customers.

In the conceptual model, the Customer represents the *Contributor* table as the contribution (comment) can also be written by a person who is not the customer of the company yet (i.e. potential customer or detractor). In a snowflake schema, it is possible to link the *Contribution* entity through the *Comment* table to the fact table *Opinion* and filter to the specific contributor. Then it is possible to find out the overall satisfaction of the contributor or their satisfaction with a particular comment, object or aspect. The fact table *Personality* is related only to the table *Comment* since the detection of the personality traits depends on the expression as a whole and does not relate to an aspect or object.

The *Comment* class stores the full content of each customer's contribution, including the date when the comment was written. The source of each comment is stored in the class *Comment_Source* with values like 'email', 'call centre', 'social media', 'review' and similar. The *Comment_Type* determines the type of the comment based on the detected information in the text – whether it is a 'requirement', 'complaint', 'compliment', 'suggestion' or 'need'. Each *Comment* is written by a *Contributor,* and the relationship is many to one since one contributor can write many comments. The *Contributor* table comes with attributes identifying the contributor based on cookies, email, name, telephone number, transaction number or other identifiers which can distinguish the author of the comment based on meta-data gained from the comment. Since some comments are not tagged with customer or account identifiers, there is no direct way to link such comments with a particular customer or account in the database. In ETL transformation, these attributes are further matched with existing information presented in the customer and account profiles, and the best match is then linked with the *Customer* table at the analytical stage. Contributors without a match get the attribute *Is_Customer_Flag* with the value ‘non-active’ in the *Customer* table (see the physical data model in Figure 5.7). The linking of customer profiles with customer interactions is an essential step in ETL as it brings together the factual information about the customer gained from structured data with the factual information gained from the textual interaction used later in Customer Experience model.

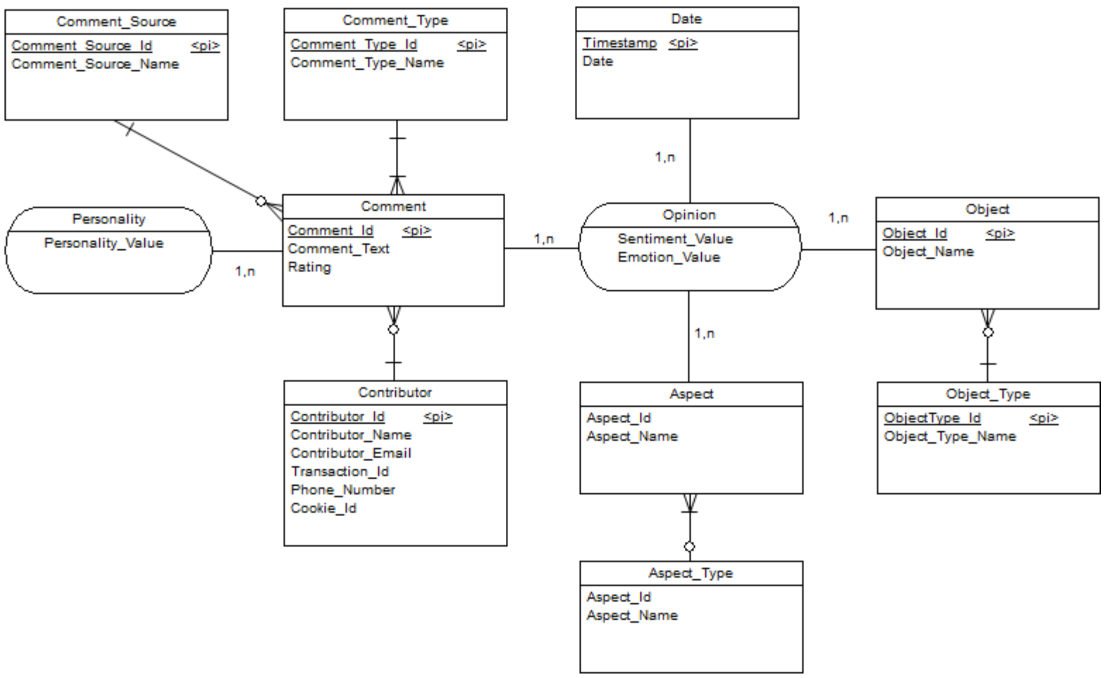


Figure 5.5: Conceptual model of the textual stage[38]

The *Object* table stores the title of the discussed ***object o***. This table can represent any entity such a ‘product’, ‘issue’, ‘service’, ‘event’, ‘person’ determined in table *Object_Type*. The *Object* table allows the model to be multi-domain since it is possible to store comments on a wide range of topics.

The ***object o*** can be recognised from the contribution based on the relation to the product/service it belongs to, metadata (i.e. review submitted to a particular product, an email regarding the product the customer purchased), the discussed domain or based on a dominant topic in the text.

The table *Aspect* stores the results from aspect detection methods. The ***aspect a*** is extracted for determined objects and represents a ‘feature’, ‘dimension of quality’,

[38] The large picture of the schema can be found in Appendix C.

'functionality' or a 'component' of the ***object o.*** Similarly to the *Object*, these types of aspects are stored in table *Aspect_Type*.

The ***aspect category*** mentioned in section 4.1.2 and 4.2 does not represent an individual entity in the relational model but is stored in the table *Aspect* to keep the simplicity of the model. Too many unique terms could not bring any added value for evaluation. The terms are possible to find in the table *Entity*, which is related to the *Comment* table (Figure 5.3).

The ***object o*** is represented by a finite set of its aspects $A = \{a_1, a_2, \ldots a_n\}$. A customer contribution (stored in the model in the *Comment* table) contains opinions about a finite set of objects $\{o_1, o_2, \ldots, o_v\}$ and a subset of aspects of each object.

The m:n relation between the tables *Object* and *Aspect* replaces the idea that the product or service, which is the subject of the comment, is always classifiable into a hierarchy or family of products or services used by some researchers (Yaakub 2015; Castellanos et al. 2010; Park & Song 2012; Lau et al. 2009). The basic idea of m:n relations between the tables *Object*, *Aspect* and *Comment* is that a negative comment about the object (product) does not mean that the customer gives a negative opinion on its aspects, or negative comment about the aspect does not necessarily mean that whole comment is negative too. Also, the same aspect can be assigned to different objects (the aspect 'battery' is associated with both the object 'mobile phone' and object 'laptop'). If the statement does not mention any aspect at all (overall experience), then the evaluation stored in the table *Opinion* is assigned to the ***object o*** in table *Object.*

The *Date* table inserts the dynamic character of the Customer Experience into the model and enables tracking information over time.

5.6.4 Physical Data Model for Textual Stage

The physical model[39] (Figure 5.7) expands the conceptual model by necessary attributes[40] and foreign keys and represents the connection to some other tables entering the analytical stage from internal sources of EIS.[41]

The fact table *Opinion* contains the information detected by text analytics methods and transformed into structured data (see Figure 5.4). The table contains an identifier to dimension tables *Comment*, *Object* and *Aspect* as the relation between these tables is m:n. The table stores

[39] The schema is designed with the modelling tool PowerDesigner 12.
[40] Author notes that not all attributes are depicted in the model.
[41] Such tables have a grey fill in the physical model in Figure 5.7.

the calculated *Sentiment_Value*, which serves in reporting for sentiment polarity determination:

- positive, if *Sentiment_Value* > 0,
- negative, if *Sentiment_Value* < 0,
- neutral, if *Sentiment_Value* = 0.

If the *Sentiment_Value* of all objects and aspects in the comment is zero and no emotions are detected, the comment is considered rational. The attribute *Rationality_Flag* in table *Comment* determines the character of the comment based on detected opinion – if the comment is 'rational' or 'evaluative'. The rationality is determined by detected emotions and sentiment in the text.

The table also contains flags for Plutchik's (1980) eight primary discrete emotions. Since there are only nine emotions, they can be labelled with the flags containing their intensity values in the *Opinion* table. If the model were expanded to more emotions from the Plutchik's Wheel of Emotions, the schema would have to change, and the relational table *Opinion_Emotion* would extend the model (Figure 5.6) as the relation is m:n – one opinion can contain more emotions.

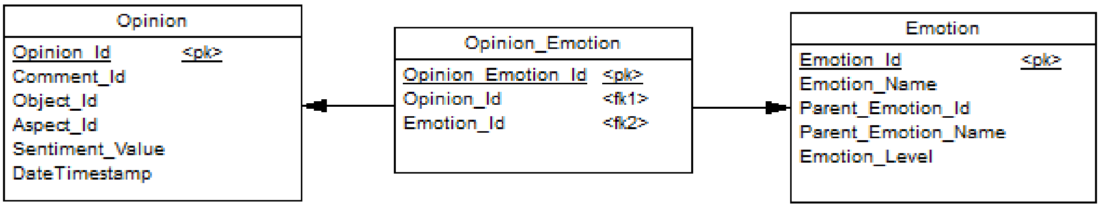


Figure 5.6: The m:n relation between opinion and emotion

As personality detection is based on whole comments, the fact table *Personality* is related to the *Comment* table only. The table stores a calculated value for every personality trait according to the Five-Factor Model (McCrae & John 1992). The values are then aggregated on customer level through related comments.

The tables from the textual stage are linked to other tables in the data model whose sources are in other systems like CRM. The relationship to dimension tables *Customer* and *Product* is depicted in the physical model. Since the table *Object* can represent any entity, such as a product or service, it is desirable to map values to the right tables according to dimension table *Object_Type*. According to this information, the *Object* table has links to other appropriate tables. It is worth noting that the model can contain more relationships based on the business case of the organisation and elements detected in the text. In this model, only the relationship with the *Product* table is presented in order to maintain the readability of the model. Additionally, in treatment validation, the table *Object* refers to the table *Product*.

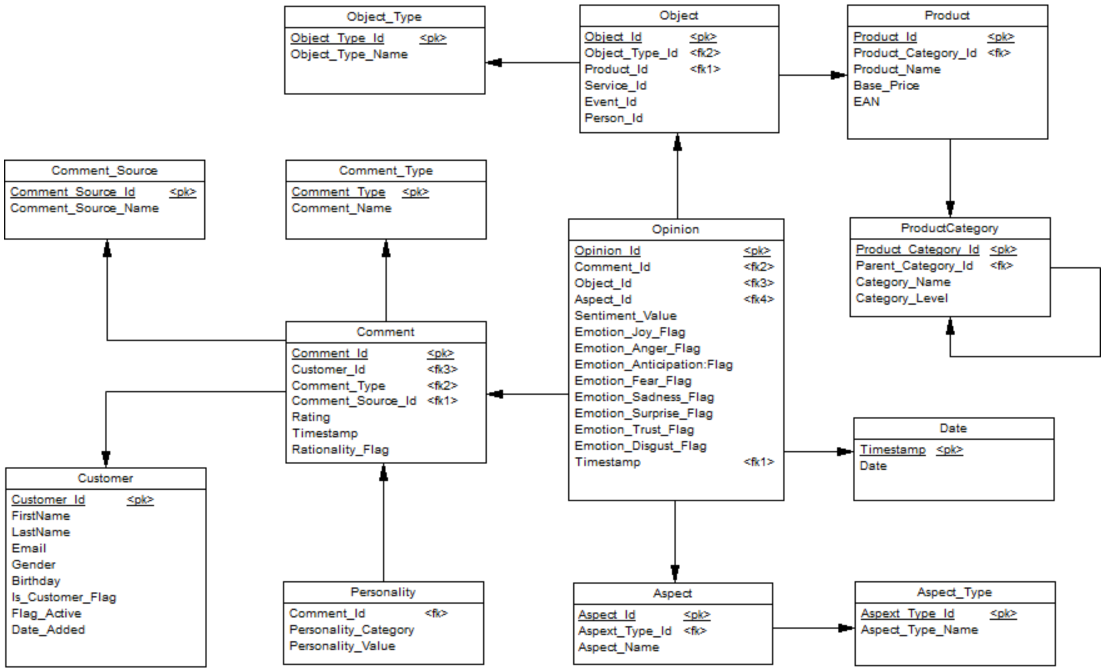


Figure 5.7: Physical model of the textual stage[42]

The mapping to the right object type is built on the similarity rules. If the value of attribute *Object_Name* in the table *Object* is found in the attribute *Product_Name* of the table *Product*, the row containing this value also gets the attribute *Object_Id* mapped to the *Object* table. The principle with other classes would be similar. Comparably, table *Aspect_Type* determines the mapping of the table *Aspect* to other internal dimension tables.

The *Customer* table replaces the *Contributor* table in the next phase, and the unidentified customers (contributors without a match – see the previous section) get the 'non-active' value to the attribute *Is_Customer_Flag* as such a contributor has not made a transaction with the company.

The customer textual data also comes with other metadata such as *Timestamp* or *Rating* if the *Comment_Type* is a 'review' (in this case, *Rating* is an attribute of the table *Comment*). *Timestamp* is an essential attribute for the reporting considering that a customer can have an inconsistent experience during the iterative customer journey described in section 2.4. The

[42] The large picture of the schema can be found in Appendix C.

table *Personality* is not linked to the *Date* table due to the assumption that the personality does not change with time. The personality prediction can be refined with additional textual data.

5.7 Analytical stage

The analytical stage of the data model builds mainly on the knowledge of Customer Intelligence and exploits tables used in analytical CRM following the designed metric in section 5.3. The analytical stage (Figure 5.8) depicts the interconnection of the textual stage modelled in Figure 5.7 with the tables typical in analytical CRM (e.g. personal information, sociodemographic data, product preferences), but also with the tables resulting from other sources of EIS:

- transactional data (orders, sales, etc.)
- campaign data (campaign costs, budgets, plans from campaign management systems)
- web data (click-stream data and other data from web analytics platforms)
- results of data mining and other analytical processes as aggregated data (e.g. CLV).

These aggregated data serve as underlying data for metrics reporting (see section 5.3 for calculation definitions). For this reason, the data model is denormalised. The denormalisation also enables easier querying for analytical purposes.

The relations to the *Timestamp* and *Date* dimensions are omitted for the intelligibility of the model. The author preserves only the relation between the *Opinion* fact table and the *Timestamp* dimension table to demonstrate the time dimension of the model. In reality, all fact tables have links to the *Timestamp* or *Date* dimension table to ensure the history maintenance with snapshots and storage in historical tables.

It is emphasised that not all tables are depicted in the model as the complexity changes based on available sources of data. The model can contain several dimensions depending on the granularity level of the measured Customer Experience. The model corresponds to a part of a complex analytical model which is linked to several other entities. It provides a data mart for a Customer Experience Measurement, which can, in turn, be extensible for new entities and attributes. The model in Figure 5.8 presents the fact and dimension tables necessary for metrics reporting listed in Table 5.1 with examples of attributes.

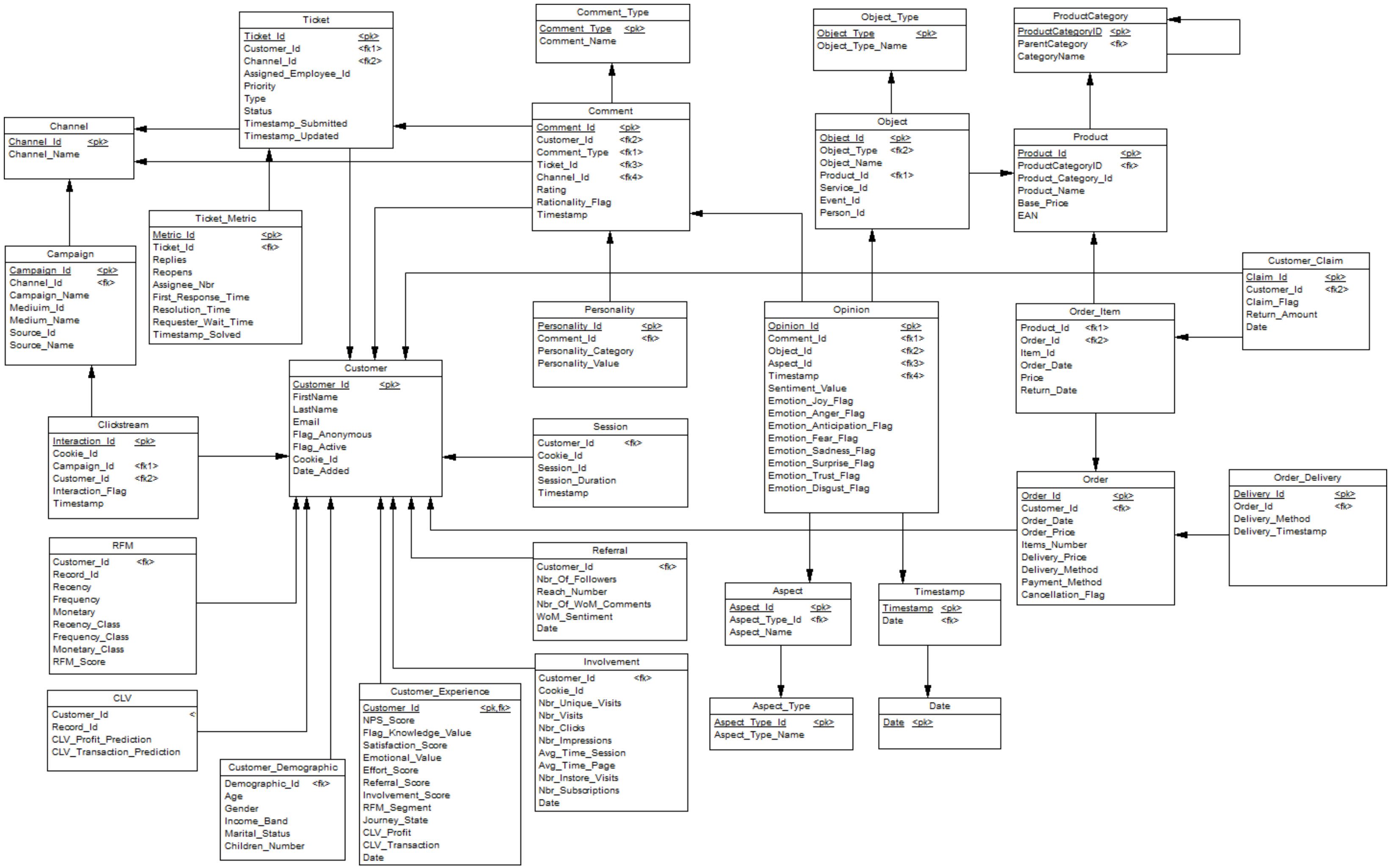


Figure 5.8: Physical model of the Analytical stage of the Customer Experience Measurement model[43]

The analytical stage presented in Figure 5.8 expands the textual stage for the following tables:

Table 5.5: Tables added in the Analytical stage

Table name	Description
Channel	The Channel dimension table replaces the Comment_Source table from the textual stage. It contains all possible channels through customer interactions, not only with textual expression. This table represents the interconnection with other sources of the data.
Campaign	The Campaign dimension table extends the Channel for another granularity which represents campaigns the customer interacts through the web. The table can have foreign keys to tables Medium, Source, Placement or Banner depends on the granularity level. If it is possible to react to campaigns with textual data, the reference from the table Comment would be modelled.
Clickstream	The Clickstream fact table collects data from web analytics tools. It represents the interactions of individual cookies with individual campaigns. The attribute Interaction_Flag determines if the interaction was click or impression. If the Cookie_Id is recognised and linked to the Customer_Id, the reference with the Customer table is linked.
CLV	In the CLV fact table are stored predictions from the CLV modelling by different CLV models – the prediction of the transactions and profit for the next period for every customer.
Customer_Claim	The Customer_Claim table stores the data about the customer's claims on purchased items. The Claim_Flag attribute determines if the claim is a replacement of the item, compensation or money return.
Customer_Demographic	The table expands the table Customer for demographical data. This table serves for segmentation customers based on demographical data.
Customer_Experience	The table Customer Experience serves for storage the results of different metrics or classifications to different segments which represent constituent elements of Customer Experience. For example, RFM_Segment is based on the results from table RFM. This table serves for easier querying to gain the results faster and preserving history values. Otherwise, these values can be found in other tables.
Involvement	The table Involvement stores the aggregated data from web analytics tools which serve as metrics. If the Cookie_Id is recognised and linked to the Customer_Id, the reference with the Customer table is linked.
Order	The Order fact table contains information about customer's orders. If the order was cancelled during the process of the purchase, the Cancellation_Flag gets the positive value. The table can contain many attributes regarding the prices, methods of payment, delivery and similar.
Order_Item	The Order_Item table represents items purchased within the Order. The table has a reference to the table Order. The attribute Return_Date would represent the date of return if the customer returned the item. The table can have many attributes with references to additional tables like Service if the item is coming with additional services.
Order_Delivery	The Order_Delivery table stores the information about the timestamp when the order was delivered to the customer. Based on this information, the average time of delivery can be calculated.

Table name	Description
Product_Category	The Product_Category dimension represents the two-level category of the products.
Referral	The Referral table stores aggregated data from social networks analysis as metrics.
RFM	The table RFM stores the information for RFM calculation – frequency, recency. Monetary values together with the assigned bin and segment. This table is a result of calculations and modelling based on the table Order.
Session	The table Session is based on data from web analytics tools and stores the information about the customer's visits on the company's websites. If the Cookie_Id is recognised and linked to the Customer_Id, the reference with the Customer table is linked.
Ticket	The table Ticket represents the customer's claim, requirement, need or complaint submitted to the company. The ticket can be composed of a thread of comments. The table has a reference to table Channel representing the channel through the customer submitted the ticket; the Assigned_Employee_Id can represent the foreign key to the table Employee (not shown in the model). The Timestamp_Submitted shows the time when the ticket was sent to the company and Timestamp_Updated records every update in the ticket.
Ticket_Metric	The Ticket_Metric table serves for a calculation of metrics based on the information from attributes of the table Ticket. The table records number of replies to every ticket (number of comments), number of reopens, how many employees were assigned to the ticket till his solution, the time till the customer had to wait to the first response to his ticket is stored in First_Response_Time, the Resolution_Time stores the total time from the first contact to the solution of the ticket. Requester_Wait_Time records the total time the customer spent waiting for the response.

5.8 Application of the Model

Table 5.6 summarises the flow of necessary steps in applying the proposed model to the real environment and its integration into the relational databases. Processes are mapped to their relevant parts in this chapter. The processes respect the architectural framework depicted in Figure 5.1. The main goal of the model is to transform the written VoC into a structured form and convert it into Customer Intelligence. The single comments are broken to sentences to look for the objects and aspects which help with the understanding of the context and to uncover the sentiment and emotions. Next, gained information is stored in the structured form in relevant tables of the textual stage, and finally, they are paired with all the transactional, demographic and behavioural data available in the company in other systems and loaded in the analytical stage. Last, the results of the metrics are visualised to the stakeholders in reports.

Table 5.6: Basic process flow for the model application

	Process	Input	Output
1.	A managerial decision what metrics and indicators to measure and track	The list of metrics proposed in section 5.3 and listed in Table 5.1	Chosen metrics from the list in Table 5.1.
2.	Crawling the source systems with the textual data and their transformation to the structure readable by relational database	Programmed crawlers to gaining the raw data from the unstructured source systems (e.g., social networks, reviews, emails, ticket systems)	Textual data in a format suitable for storage in a relational database according to section 5.6.1
3.	Identification of the authors of the comments and their linkage to the current customer base	Textual data in a format suitable for storage in a relational database Structured data about the customers from the internal systems	The relation between the comments and the customers, if it exists
4.	Pre-processing of the comments: spell-check, lemmatisation, tokenisation, PoS and syntactic dependencies detection	Comments stored in the relational table with their meta-data	Relational table with pre-processed data as shown Table 5.4 in section 5.6.2
6.	Text analytics (content analysis) - Sentiment analysis - Emotion detection - Personality detection	Relational table with pre-processed data Dictionaries and lexicons for text analytics stored in the relational table	Results from text analytics stored in the pre-textual stage as a semi-structured data according to section 5.6.2 and Figure 5.4
7.	Loading the textual stage	Results from text analytics stored in pre-textual stage	Relational tables containing the information gained by text analytics described in section 5.6.3 and model depicted in Figure 5.5
8.	Linking the tables in the textual stage to tables from the internal systems (data warehouse)	Relational tables containing the results from text analytics Relational tables from the internal systems	Loaded textual stage according to section 5.6.4 and model depicted in Figure 5.7
9.	Loading the analytical stage	Loaded textual stage Relational tables from the internal systems Data mining results	Loaded analytical stage according to section 5.7 with pre-calculated metrics
10.	Metrics visualisation	The analytical stage	Metrics visualised in reports according to dimensions proposed in Table 5.2

5.9 Benefits of the Customer Experience Data Model

The Customer Experience data model and the subsequent measurement bring the following benefits significant for Customer Experience Measurement and Management. The benefits are further discussed in Chapter 6 and Chapter 7 during the artefact's validation.

1) The model represents the application of the Customer Experience construct. The Customer Experience data model can help with a scope definition of measures.
2) The model enables to measure the experience during the customer journey thanks to data collection across different touchpoints with the time dimension.
3) The model is multidimensional and enables to monitor the elements from different viewpoints; dimensions allow querying specific subsets of data. Data which contain the specific forms of searched objects, aspects or comments are then displayed.
4) The model is extensible and transferable to any business environment. New entities, attributes and related metrics and dimensions can always be defined. Connectors for new sources of data can be added.
5) Due to the consistency with other trusted data in unified storage, the integrated data model guarantees higher credibility and accuracy of textual VoC and its subsequent measurement, which in the Internet environment may not be satisfied. The consolidation enables reducing random, time-consuming and prone-to-error processes with the less human effort, which is challenging to scale with the growing data.
6) The model reflects the customer perspective of the opinion target while the product perspective is not omitted. It is possible to aggregate the sentiment according to the particular object or aspect based on all comments from all customers who mentioned that aspect in these comments.
7) Long-term monitoring of metrics within the consolidated reports allows finding patterns in Customer Experience and taking the corresponding approach or prevent certain situations. The close co-operation of analysts and stakeholders is necessary. Stakeholders must understand the essence of the metrics to be able to work with them correctly. This approach leads to continual improvement of Customer Experience and growth of agility, profitability and orientation to the customers.
8) The artefact mitigates the barriers (numbered as barrier 1-6 in section 3.3.3) in achieving the full potential of analysing VoC within Customer Experience detected by participants of the qualitative research in Chapter 3 (see section 3.3.3):

a. The model enables the necessary integration of textual VoC from various channels and links this data to operational data, data from web analytics and other sources at one consolidated place accessible to all stakeholders. The textual part of the model (see 5.6.3) for storing the information from textual content leverages the use of insight gained from textual VoC within the share-of-mind metrics and significantly simplify the sharing of knowledge throughout the organisation. *(barrier 1, 3)*

b. The share-of-mind metrics are evaluated from these data and shared throughout the organisation in consolidated periodical reports. For business users, the reporting of metrics on dashboards brings the visibility and clarity of all monitored metrics and their instant overview of improving or deteriorating. *(barrier 1)*

c. The view on customer becomes unified, and his data stored in fine granularity at the individual level enable targeted one-to-one actions. *(barrier 4, 5)*

d. The connection to other financial data such as purchases, marketing costs, the performance of the channels and similar help to prove the financial results of Customer Experience actions. *(barrier 2)*

e. The model enables employees to communicate with the customer consistently through all channels based on shared knowledge within the organisation. *(barrier 4)*

f. The model brings a certain formalisation to Customer Experience Measurement and management. The model helps with a scope definition of measures and metrics. *(barrier 6)*

5.10 Chapter Summary

This chapter represents the main contribution to the dissertation as it brings the artefact of the Customer Experience Measurement model in the form of two deliverables: *D1: The Customer Experience data model* and *D2: Set of metrics evaluating Customer Experience from the customer's perspective based on elements of sentiment, emotions and personality traits*. The process of integration of textual data to the structured environment also contributes to the answer of *RQ2* and is described with three stages of the data model: pre-textual stage, textual stage and analytical stage representing the Customer Experience data model within the BI framework (Figure 5.1).

First, the list of dimensions and metrics for reporting are defined based on the literature research and interviews results. Second, the data model is built to reflect the designed metrics as unified storage to access the tables for the metrics results or calculations. The data model is built to fulfil the designed minimal requirements in section 5.2. The model is extensible and transferable to any business environment. New entities, attributes and related metrics can always be defined.

The chapter described the process of the opinion target extraction from the textual VoC, and its storage in the model with the detected sentiment, emotions and personality traits. This information is further combined with other information gained from structured data based on Customer Experience metrics to recognise its constituent elements. The basic steps in the application of the model are summarised in Table 5.6.

The data model is multidimensional and enables to monitor the elements from different dimensions. One of the main contributions is the customer perspective of the opinion target. The advantage of the customer perspective in the data model is that the product perspective is not omitted. The other benefits of the Customer Experience data model are listed in section 5.8. The model also mitigates the barriers of getting the full potential of analysing VoC within Customer Experience detected by participants of the qualitative research in section 3.3.3.

The integration of textual data with the customer data from CRM, web analytics and other marketing tools brings greater knowledge about customers but also covers a broader spectrum of information for an enterprise and marketing efforts. The model represents possibilities to achieve a cohesive and comprehensive view of the customer. It can adjust marketing practices to establish the correct approach to the customers consistently across all channels and reach the right person at the right time with the right content and settings. The examples of the impact of Customer Experience Measurement to marketing activities are mentioned further in section 6.2.6.3. Following two chapters focus on the validation of the artefact.

Chapter 6

Validation of the Artefact with the TAR Method

This chapter brings the conceptualisation and validation of the textual stage of the designed Customer Experience data model and related metrics by their implementation into a real-world context in a case study. Following TAR (see section 1.4.3), the author designs treatment in an e-commerce environment of one of the companies interviewed in Chapter 3. The researched company agreed to be involved in the validation of this research to fulfil their specific goals and to learn about its effects in practice. The study encompasses the implementation of text analytics methods for aspects detection, customer satisfaction measurement, and emotion and personality detection. The results of the applied text analytics of provided data are integrated into the Customer Experience data model, and the Customer Experience metrics are calculated. The text analytics methods follow the CRISP-DM as a methodological framework (Šperková & Feuerlicht 2017).

This chapter brings the deliverable *D3: Application of text analytics methods suitable for determining and measuring Customer Experience elements based on VoC textual data* as a fulfilment of objective *O3*. The chapter also contributes to research question *RQ2* and partly to *RQ3* as the treatment implementation, and evaluation in the real business environment brings managerial implications to the Customer Experience Management by assessing the achieved effects in the company. This assessment is provided by a qualified person in the company who has in-depth knowledge in the area of analytics and management of marketing activities and who will be introduced to the treatment results. Any comments received within the feedback will be incorporated into the treatment.

6.1 Problem Investigation[44]

The researched company is an e-commerce company located in Prague with less than ten internal employees and ten external employees or consultants. The company has been in the market for ten years and has tens of thousands of customers. The company sells experiences as an intermediator for more than two hundred providers of experiences in the Czech Republic. The term "experience" usually refers to a short-term event, trip or session, focused on

[44] This section corresponds according to CRISP-DM methodology to the Business Understanding phase.

significant Customer Experience. Such an example could be parachute jumps, sightseeing flights or diving trips.

First, the customer purchases an experience from the company's website, and the company issues a certificate to the customer. Second, the customer who purchased the certificate or the person who received the certificate reserves the date of the event. On the date of the execution, the consumer redeems the certificate with the provider, which arranges the execution of the purchased certificate in its location. That means that the company acts as an intermediator and the sales model is different from the traditional models of ***purchase → consummation to certificate purchase → booking of the product → execution***. For example, the customer purchases a sightseeing flight from another provider (flying club, private flying company) from the company; the company delivers a certificate for the customer, and the company also arranges everything needed to book the required date for the customer. The actual execution of the experience then takes place at the location of the provider (in this example, the airport). An important specificity of this model is that the person who purchases the product does not have to be a consumer of the product at the same time.

The company describes itself as a novice in Customer Experience Measurement. The company evaluated VoC in a structured form for marketing purposes with attempts to monitor Customer Experience Measurement with customer satisfaction and loyalty by ad-hoc reporting based on manual evaluation of the textual data. The company collects textual VoC based on automatically distributed satisfaction questionnaires (a few days after the event execution) in the form of customer reviews. Another potential source of textual data is chat and email communication, but the company does not collect these data yet. The company does not systematically evaluate any textual data, only perform ad-hoc manual analyses.

The stakeholders of the company are interested in the automatic evaluation of customer reviews. These reviews are a combination of category evaluation in the form of numerical Likert-type scale ratings accompanied by short textual comments about the experience[45].

The stakeholders are the company's internal employees, external employees and consultants:

- Chief Executive Officer who needs the overview of the company's performance,
- Product manager managing the experience providers,

[45] The data are described in section 6.2.1 Data Understanding.

- Marketing Manager,
- BI data analyst who ensures the overall company data strategy and makes sure important data/information reaches the right company employees,
- Customer support employees directly communicate with the customers through various channels. They handle orders, issue certificates and make reservations,
- The third-party consultants delivering specific marketing reports according to company’s needs.

The defined stakeholders’ goals relate to the mitigation of the barriers to get the full potential of analysing VoC within the Customer Experience. The main goals are:

SG1) Incorporation of customer reviews to the current Business Intelligence data model and creation of the textual part of the Customer Experience data model

SG2) To automatically report information from customer reviews next to other available customer data in consolidated Customer Experience Measurement.

In the next sections, the criteria are defined to contribute to the fulfilling of these goals.

6.2 Treatment Design

The treatment design represents the artefact from Chapter 5 in the environment of the stakeholder company. To fulfil the stakeholders’ goals *SG1* and *SG2*, the author specified the following criteria to contribute to predetermined goals:

1) To implement the textual data stage to existing BI data model and fill it with data based on the information gained from customers reviews.
    a. To automatically detect the aspects in the comments.
    b. To assign the sentiment (to detect satisfaction) to single aspects.
    c. To assign the emotions to the comments (aspects).
    d. To assign personalities to customers (only as an experiment without validation)
2) To expand the textual stage to the analytical stage to gain the complete Customer Experience data model in order to monitor the Customer Experience measures according to Table 5.1: Metrics and Indicators in Customer Experience Measurement.

3) To propose reports/dashboards based on the Customer Experience metrics and indicators from Table 4 with using dimensions from Table 5.2.

4) To propose the following marketing actions based on the suggested metrics from Table 5.1.

6.2.1 Data Understanding

In the Data Collection task was necessary to specify the data sources and how the acquisition will be carried out. The company has its tailored ERP system running on a PostgreSQL database. The author gained access to this database. In the first phase, the author designed, developed and implemented the data warehouse based on the operational system to be able further work with data in the required structured form (see Appendix C, Figure C.5). The textual information in the form of reviews is stored in a structured table and saved in the database. The textual input data represent customers' reviews of purchased products (experiences[46]). After the date of the reservation of the product, the consumer of the product (it is not necessarily the person who bought the product) has an opportunity to evaluate the purchased product. The input table contains the attributes listed in Table 6.1.

Table 6.1: The pre-processed input table with customer's reviews[47]

Attribute	Description	Value
Review_Id	Unique identifier for the review	Integer (Primary key)
User_Id	Unique identifier for the user	Integer (Foreign Key to the table User – optional reference)
Reservation_Id	Unique identifier for the reservation	Integer (Foreign Key to the table Reservation – mandatory reference)
Rating	The average from Answer 1 - 4	Decimal
Recommendation	The answer whether the user would recommend the experience in scale	Decimal: values 0.25 / 0.50 / 0.75 / 1.00
Improvement_Proposal	Suggestions for improvement in free text	Text
Pros	What user did like in free text	Text
Cons	What user did not like in free text	Text
Purchase	Who purchased the product	1 - I bought the experience myself 2 - I received the experience as a gift, but I chose it by myself 3 - I received the experience as a gift, selected by someone else 4 - Other option

[46] The author will refer experiences as products to avoid confusing concepts futher in the text.
[47] Data description step according to CRISP-DM.

Attribute	Description	Value
Purchase_Note	The reason for product purchase in free text	Text
Not_Attended_Note	The reason for not participating in experience in free text	Text
Answer_1	Satisfaction with personnel on scale	Decimal: values 0.25 / 0.50 / 0.75 / 1.00
Answer_2	Satisfaction with the location and environment on scale	Decimal: values 0.25 / 0.50 / 0.75 / 1.00
Answer_3	Satisfaction with the reservation term on scale	Decimal: values 0.25 / 0.50 / 0.75 / 1.00
Answer_4	Satisfaction with price/value ratio on scale	Decimal: values 0.25 / 0.50 / 0.75 / 1.00
Date	Posting date	Date
Flag_Is_Customer	Is the reviewer a customer? (existence of foreign key to the User table)	Integer: 0 – no / 1 – yes
Experience_Title	The name of the product	Text

6.2.1.1 Data Exploration

The table *Reviews* contains 8,904 records. The reviews are predominantly small, paragraph-sized posts with non-formal language. Attributes *Cons, Pros, Improvement_Proposal, Purchase_Note and Not_Attended_Note* contain data in free text. These attributes are candidates for textual analysis.

The attributes *Recommendation, Rating and Answer_1 – Answer_4* contain a numerical evaluation of the satisfaction with the product on an ordinal scale, where *Recommendation* and *Answer_1 – Answer_4* acquire values 0.25, 0.50, 0.75 or 1.00, *Rating* is then the average of values from attributes *Answer_1 – Answer_4.* The histogram of the attribute *Rating* depicted in Figure 6.1 shows that positive rating prevails in the dataset.

The column *Pros* is filled in 6,561 cases, column *Cons* in 3,736 cases, *Improvement_Proposal* in 2,012 cases. The column *Purchase_Note* is filled in 339 cases and does not contain the information to who was the product gifted or by whom it was purchased. The *Not_Attended_Note* is filled only in 74 cases. A treatment design will experiment with the columns *Pros*, *Cons* and *Improvement_Proposal.*

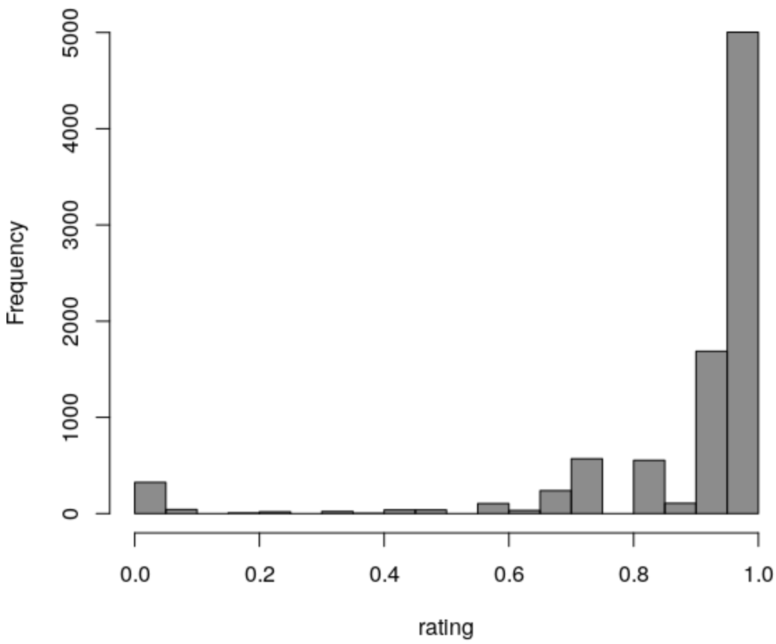


Figure 6.1: Histogram of the attribute Rating

In many cases, the reviewers filled the column *Cons* representing the answer to the question "What I did not like" with answers like *"No"*, *"Nothing.", "I like everything", "x"*, *"Everything OK", "I can't complain"* and similar when they had not had a negative experience. The positive statements such as *"Everything was great"* should be labelled as positive. Similarly, in the column *Improvement_Proposal*, statements such as *"No"*, *"Nothing"*, *"I liked everything"* do not contribute to any proposal and should be removed.

6.2.2 Pre-processing[48]

In the first place, the textual fields of the table have must be pivoted to a single column. The result got 12,390 textual rows. The pre-processing phase contains the pre-processing and cleaning techniques improving the performance of the models:

- Spell-check
- Tokenisation
- Lemmatisation
- Part of Speech (PoS) tagging
- Dependency parsing
- Negation flag
- Definition of stop-words

[48] This section corresponds to Data Preparation phase according to CRISP-DM methodology.

The pre-processing phase was performed using the programming language R. As the data come from real-world reviews, they contain missing diacritics, various typos and spelling errors, ad-hoc shortcuts, incorrect punctuation, sentence deformed, slang expressions, abbreviations or multiple languages. The author performed the spell-checking with the help of the statistical tool Korektor (Richter et al. 2012). This step was essential to get the correct lemmas in the next step. The script in R first asked Korektor REST API[49] using the model "Czech diacritics generator", which corrected the comments without diacritics. Second, it performed the model "Czech spellchecker" which corrected the other typos.

The author created a list of exceptions from the spell-check such as domain-specific words, which are unknown to the Korektor's dictionary, and named entities, which should not be corrected. The words contained in the exception list is made based on the list of the products' names and their descriptions as it contained specific words such as *bungee jumping, bodyboarding, flyboard* and others coming mainly from different languages.

The tokenisation, lemmatisation, PoS tagging and dependency relations were processed after spell-check using the Czech Universal Dependencies 2.3. Model retrieved from R library 'udpipe' (Wijffels et al. 2019)[50]. The results of the functions were converted and saved as a data frame in a structured form according to the description in section 5.6.2. The sample dataset of 8,904 records was parsed to 180,830 tokens. A negation flag was detected based on the dependency relations and saved in the separate column *Negation_Flag*. Stop-words are implicitly omitted with the syntactic rule-approach and lexicon-based approach applied in the modelling phase.

6.2.3 Manual Annotation[51]

The manual annotation of the comments corresponds to the data construction task of the CRISP-DM. The annotators manually detected the aspects of the objects in individual comments. The objects are given by the product name identified by a unique identifier in the *Experience* table. Following examples from a given dataset show an object representing the experience "*flight with the glider*". Annotators intended to detect the aspect terms in every sentence of the comment. Aspects were selected from the open set according to the annotator's

[49] Available at https://lindat.mff.cuni.cz/services/korektor/api-reference.php. The Korektor is maintained by Institute of Formal and Applied Linguistics, Faculty of Mathematics and Physics, Charles University, Czech Republic.
[50] Documentation available at https://cran.r-project.org/web/packages/udpipe/udpipe.pdf
[51] This section corresponds to the Data Preparation phase according to CRISP-DM methodology.

opinion. Based on the detected aspects, the sentiment polarity (negative, neutral, positive) was assigned for evaluative statements:

Nádherný bezmotorový tichý let s příjemným pilotem.
(Wonderful quiet glider flight with a pleasant pilot.)

- *let (flight): sentiment: positive, pilot (pilot): sentiment: positive*

Let mohl být delší.
(The flight could have been longer.)

- *let (flight): sentiment: negative*

Next, the detected aspects were grouped under the aspect categories if desired. In the example of *"flight with the glider"*, the aspects *instructor* and *pilot* in two above mentioned sentences can be grouped into category *personnel*.

The annotators were divided into 18 pairs and independently manually annotated 1,663 contributions from column *Cons* following given guidelines. The *Cons* column was chosen because of its problematic nature as contributors have often tendency to fill this column with positive statements. If the sentence did not contain any appraisal word but only aspects, it was assigned with negative polarity according to the purpose of the *Cons* column. If the sentence did not contain any aspect, it was assigned to the aspect *general*.

The result showed that human annotation was successful in case of detecting sentiment polarity (the inter-annotator agreement was a little over 0.86 by Cohen's Kappa[52] in polarity assignment). Aspect detection has proved a difficult task. Annotators agreed only in 37% of cases. The reason was the open set of aspects to choose. The annotators assigned different synonyms to the aspects with same meaning or interpreted the meaning differently, mostly in cases where the aspect was represented as a phrase composed of several words or represented an abstract notion. In these cases, the annotator's interpretation differed. For example, in the case of *"Bylo to moc krátký." ("It was very short.")*, the first annotator detected the aspect as *"čas" ("time")*, the second annotator as *"doba" ("period")*. Other inconsistencies occurred in case of sarcasm, irony or present emoticons, which some annotator considered in polarity detection and others not. Thus, a control person was chosen to check annotated records to select a single version.

[52] Cohen's Kappa measures the agreement between two annotators each of whom classifies X items into Y mutually exclusive categories; see also (Veselovská 2017, p. 135).

The annotators assigned a neutral polarity to 26 contributions, positive polarity to 526 contributions, and negative polarity to 1,111 contributions. Altogether, the annotators detected 614 unique aspects.

6.2.4 Syntactic Rules Specification[53]

The syntactic rules detected by PoS and dependency relations are mostly usable in aspect detection. Table 6.2 shows the list of syntactic rules previously defined in (Veselovská & Tamchyna 2014) with the examples of the sentences from the company's dataset. In this thesis, these rules are enriched for the dependency relations of the words representing the aspects and the evaluative part. The detected dependency relations are supposed to serve as rules for the analysis of the given corpus.

Table 6.2: List of syntactic rules

Description of the rule	**Example**
Actor or patient of a verb with a subjective adverb.	*Doba zážitku uplyne příliš rychle.* *(The experience time will pass too quickly.)* *Aspect: Doba zážitku (nsubj + nmod)* *Evaluative part: příliš rychle (advmod + advmod)*
Nouns modified by subjective adjectives.	*Ne příliš vhodný pokoj.* *(Not a very suitable room.)* *Aspect: pokoj (noun, root)* *Evaluative part: ne příliš vhodný (advmod:emph + advmod + amod)*
Subject of a clause with a subjective patient.	*Instruktor měl výjimečný přístup.* *(The instructor had an outstanding approach.)* *Aspect: přístup (obj)* *Evaluative part: výjimečný (amod)*
Patient of a transitive evaluative verb.	*Líbil se mi celý seskok.* *(I liked the whole jump.)* *Aspect: seskok (nsubj)* *Evaluative part: (verb, root)*
Actor of an intransitive evaluative verb.	*Pivo na cestu domů potěšilo.* *(The beer for the journey home pleased me.)* *Aspect: pivo (nsubj)*

[53] This section corresponds according to CRISP-DM methodology to the Data Preparation phase.

Description of the rule	Example
	Evaluative part: potěšilo (verb, root)
Predicative nominal (patient).	*Nejlepší část byl volný pád.* *(The best part was the free fall.)* *Aspect: volný pád (amod + obj)* *Evaluative part: nejlepší (amod)*
Subject of predicative adjectives.	*Létání by mohlo být levnější.* *(Flying could be cheaper.)* *Aspect: létání (nsubj)* *Evaluative part: mohlo být levnější (verb, root + cop + xcomp)*
Words coordinated with an aspect are also aspects.	*Líbilo se mi prostředí, čistota, profesionalita, chování personálu.* *(I enjoyed the environment, cleanliness, professionalism, the behaviour of the staff.)* *Aspects: prostředí, čistota, profesionalita, chování personálu (nsubj + punct +conj + punct + conj + punct + conj + nmod)* *Evaluative part: líbilo (verb, root)*
Words coordinated with an aspect with 'but' should be marked with opposite polarity	*Zážitek byl naprosto úžasný, ale krátký.* *(The experience was absolutely amazing but short.)* *Aspect: zážitek (nsubj)* *Evaluative part: naprosto úžasný, ale krátký (advmod + adj, root + punct + cc + conj)*

Based on the syntactic rules, the author detected as aspects only words and phrases with following dependency relations and PoS:

- noun, which is nsubj or nmod
- nsubj (noun) + nmod *(let vznášedlem)* – both nouns are part of one aspect
- noun + conj + noun *(zážitek i personál)* – both nouns are aspects
- noun + punct + noun *(prostředí, čistota)* – both nouns are aspects
- root (noun) + nmod (noun) *(vyřízení formalit)* – both nouns are part of one aspect
- noun + adp + noun: e.g. root (noun) + case + nmod (noun) *(domluva na termínu)* – all words are part of one aspect
- amod + noun when amod is not an evaluative adjective *(celková atmosféra)*

- nmod + nmod + case + nmod *(realizace sestupu do podzemí)* – all words are part of one aspect
- nmod + amod + case + obj (noun) *(kurz zaměřený na vaření)* – all words are part of one aspect
- noun + case + amod + nmod *(procházka v zámeckém parku)* – all words are part of one aspect
- csubj (verb) + obj (noun) *(objevovat okolí)*

The author notes that there can exist more rules; however, chosen rules are more represented by a given dataset. As stated in (Veselovská 2014b), different PoS have a different influence on the sentential polarity which is closely connected to their syntactic positions in the given structures. Verbs play more of a crucial role in terms of emotional meaning than nouns, which are more frequent in the lexicon and represent mostly aspects. An adjective modifying a noun (amod) is always more influential towards sentential polarity. The author omitted these appraisal PoS from the phrases representing the aspects.

6.2.5 Modelling and Results

In the modelling phase, the author used a free software package R Studio to perform modelling in programming language R and further SQL language to work with relational tables and assigning emotions and sentiment by lexicon-based methods. The methods performed over the pre-processed dataset consists of the following steps:

1) Detection of objectivity or subjectivity of the contributions
2) Assigning sentiment to the contributions
3) Detection of aspects in the text
4) Categorisation of the aspects to aspect categories
5) Assigning emotions to the contributions
6) Detection of the personality traits from the contributions

Due to the characteristic of the contributions, the author decided to model the sentiment and emotions on sentence-level supposing that one sentence evaluates one opinion target even when it is composed of many aspects. The personality is modelled based on all contributions belonging to the same user.

6.2.5.1 Sentiment with Lexicon-Based Classifier

The lexicon-based approach was performed to assign sentiment. First, the available Czech lexicons with appraisal words[54] were merged into a unified lexicon with polarities and joined in a table with pre-processed data based on corresponding tokens or lemmas.

Second, the coverage of the lexicon was examined to find out how often a lexicon entry occurs in the data and how many distinct lexicon entries appear in the data. In the 20,642 unique tokens contained in the corpora, 10,238 unique words were found in the lexicon, that is 49.6% of tokens. 4,597 unique tokens were labelled as positive, 2,590 as negative. The rest of the tokens were assigned as neutral. The tokens not found in the lexicon were also assumed to neutral. The result is that if any single token contains any polarity, it is then assigned to the token. The negation-marked lemmas were considered as reversing the polarity of that lemma.

Most opinion mining research uses adjectives as the main terms to determine the orientation. The lexicon-based method also enables the use of other PoS such as verbs and adverbs. The dependency relations assist in the process of assigning the appropriate appraisal word to the correct subject regarding the context – a difficult task with standard classification methods. The advantage of dependency relations is that the sentiment is analysed not only in a pair of a noun with an adjective but also based on whole phrases. The classifier simply aggregates the polarity indicators of all tokens in a given level of analysis. The target detection is described further in section 6.2.5.3.

Based on the character of the contribution, the sentence-level of assigning the sentiment was chosen. The resulting sentiment value is the average of all non-zero values for every sentence. At the same time, the emoticons in the individual sentences were detected with a regular expression and saved in a separate column *Emoticon_Flag*. If the sentence contains an emoticon, it can reverse or neutralise the polarity of the sentiment or can be used as an intensification of the sentiment. A negative emoticon combined with a negative sentiment value or a positive emoticon combined with a positive sentiment intensifies the sentiment. A positive emoticon combined with a negative sentiment or a negative emoticon combined with a positive sentiment reverse or neutralise the sentiment based on from which column (*Pros*, *Cons* or *Improvement_Proposal*) the sentiment is coming. The sentences assigned with a neutral sentiment are then supposed as objective statements.

[54] Czech Sublex 2.0 and NRC was merged with NRC Word-Emotion Association Lexicon and Afinn.cz lexicon downloaded from https://github.com/vilemr/affin.cz.

The lexicon-based approach was compared with the results from the commercial text analytics tool Geneea[55] with Pearson's chi-square test of independence for polarity and paired two-sample t-test for the sentiment (results in Table 6.4). The stated hypothesis H_0 is that the lexicon-based approach assigns similar sentiment and polarity as a commercial approach.

The statistical information in Table 6.3, boxplots in Figure 6.3 and histograms in Figure 6.2 compare results of polarity and sentiment detections with the lexicon-based approach to results from commercial software Geneea. From the results, it is clear that Geneea tends to assign more neutral polarity and its results are balanced in case of mean and median, and that the lexicon-based approach determines more positive results with skewed histograms and higher mean and median.

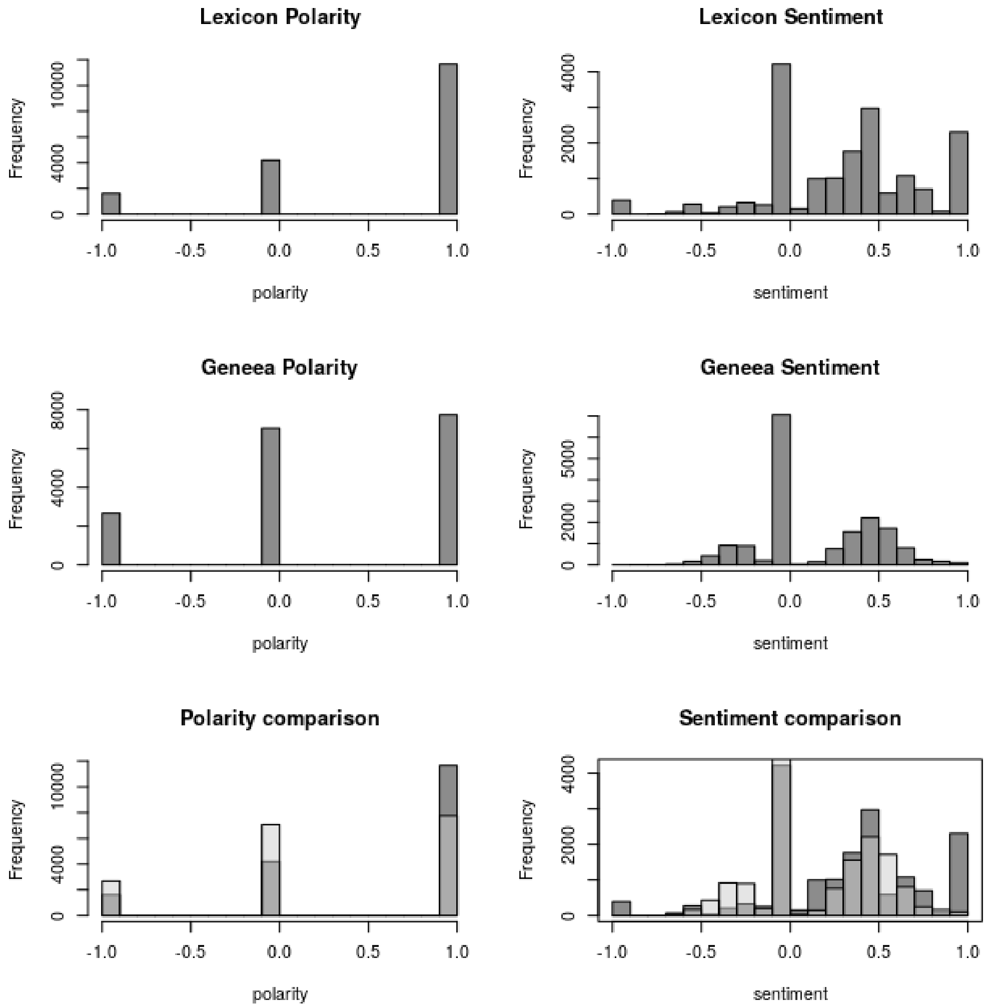


Figure 6.2: Comparison of histograms of polarity and sentiment

[55] More information about sentiment analysis in Geneea is available at https://help.geneea.com/api_general/guide/sentiment.html#x3-guide-sentiment.

Table 6.3: Descriptive statistics of measured sentiment

	Geneea approach	Lexicon-Based Approach
Polarity = 0	7,055	4,187
Polarity = -1	2,669	1,614
Polarity = 1	7,751	11,674
Sentiment mean	0.16	0.33
Sentiment sd	0.32	0.43
Sentiment median	0	0.33
Sentiment range	1.86	2
Sentiment skew	0.04	0.46
Sentiment kurtosis	-0.7	0.63

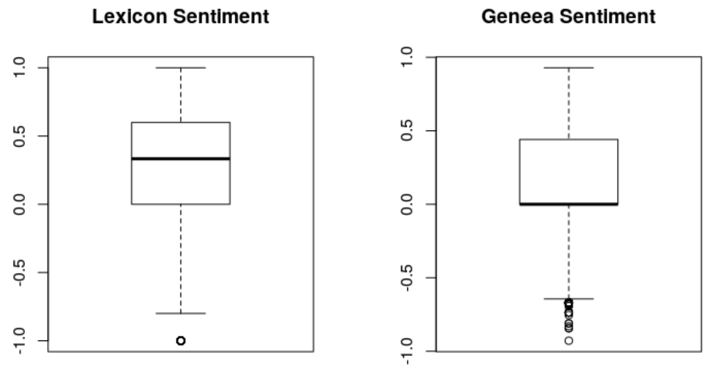


Figure 6.3: Comparison of boxplots over measured sentiment

Table 6.4 presents the results of correlation, chi-squared test and t-test. The correlation analysis (Corr) has proven a medium positive correlation between the observed approaches. According to the t-test, the p-value is nearly zero and the 95% confidence interval of the difference does not contain a zero; the hypothesis H_0 is denied. The lexicon-based approach does not assign the same sentiment as a commercial tool. The chi-squared test showed similar results with the same p-value; the hypothesis H_0 of similar assigned polarity is also denied. The conformity in assigning polarity was 62%. The reason for such difference can also be explained since Geneea generates sentiment on a sentence-level; the lexicon-based approach was aggregated on sentence-level from the polarity gained at the feature-level.

After the more in-depth analysis, it was found out that lexicon-based approach assigns sentiment even to sentences not containing the appraisal words but containing only aspects. In sentiment lexicon, there are also terms which are nouns and carry the sentiment. As reviewers answer the question "What I did (not) like", they sometimes only list things they (do not) like as nouns without evaluative words. To these contributions, Geneea assigns neutral polarity.

Based on the author's domain knowledge, it was possible to adjust sentiment without evaluative words according to their categorisation to the *Pros* or *Cons* columns.

Table 6.4: Results of paired two-sample t-test over sentiment and chi-square independent test over polarity

					95% Confidence Interval of the Difference		
	Corr	**Paired T-test**	**Df**	**p-value**	**Lower**	**Upper**	**Mean of diff**
Sentiment	0.5038	58.324	17,474	p-value < 2.2e-16	0.1633	0.1747	0.1690
	Corr	**Chi-square test**	**Df**	**p-value**			
Polarity	0.4468	4,867.7	4	p-value < 2.2e-16			

Additionally, the author compared the results from the lexicon-based approach with 1,663 manually labelled contributions. Pearson’s Chi-squared test (p-value = 3.395e-12) confirmed the hypothesis that manual tagging generated similar sentiment as the lexicon-based approach.

Lastly, the polarity of the contribution was aggregated at the document-level and compared according to categorisation to the column. There are 6,561 contributions in the column *Pros*, the lexicon-based approach categorised as positive 4,528 contributions and Geneea 3,470. The column *Cons* contains 3,736 contributions; lexicon-based approach assigned negative polarity in 1,817 cases, Geneea assigns negative polarity to 765 contributions. It can be derived, that lexicon-based approach hits the category with the polarity better than Geneea (in 69% in pros and 49% in cons). However, as mentioned earlier, the categorisation to the column does not necessarily infer the polarity itself (see section 2.3). The human annotation of 1,663 *Cons* contributions resulted in positive polarity in 44%.

The quality of the lexicon-based approach was further assessed based on a labelled Czech aspect-level sentiment corpus containing data from restaurant reviews (Steinberger et al. 2014) with a confusion matrix. The corpus contains 2,149 sentences where 2,080 sentences are labelled with aspects, categories and polarities. As the polarity is assigned to single aspects, the author aggregated the results of polarity categorisation on a sentence-level similarly to lexicon-based approach by averaging of all non-zero values for every sentence. Validation of the results gained by lexicon-based approach is based on measuring the performance metrics of precision, recall and F1-score (see Table 6.6) using the confusion matrix (Kohavi & Provost 1998) in Table 6.5. The overall accuracy is 0.63, but as the dataset is unbalanced, F1-score was measured with the result of 0.61. In Table 6.6 are listed the results of the performance metrics for every single category. The lexicon-based approach is best in assigning positive emotions with F1-score of 0.78.

Table 6.5: Confusion Matrix with categorisation results

		Predicted			
		Negative	**Neutral**	**Positive**	**TOTAL**
Actual	**Negative**	True Negative **367**	False Neutral **92**	False Positive **332**	791
	Neutral	False Negative **60**	True Neutral **243**	False Positive **173**	476
	Positive	False Negative **38**	False Neutral **68**	True Positive **707**	813
	TOTAL	465	403	1,212	2,080

Table 6.6: Performance metrics of the lexicon-based approach

	Precision	Recall	F-Score
Negative	0.46	0.79	0.58
Neutral	0.51	0.60	0.46
Positive	0.87	0.70	0.78

6.2.5.2 LDA for Aspect Category Detection

LDA method was chosen to detect aspect categories to satisfy requirements placed in section 4.2. The author performed the WarpLDA, modification of LDA implemented in R package *text2vec* (Selivanov & Wang 2016). Warp LDA achieves both the best O(1) time complexity per token and the best O(K) scope of random access (Chen, Zhu & Chen 2015).

The method models over the whole corpora (set of all contributions) as an input and results in a non-linear generative probabilistic model that contains latent topics characterised by a specific distribution of words in documents (individual contributions). This method can model unknown aspects and categorise aspects. The results are aspects prevailing in all comments; the method does not take comment after comment and retrieves the aspects.

The several hyper-parameters needed to be set on the input: number of topics, document-topic prior and topic-word prior. The hyper-parameters were set to lower numbers to prefer sparse topic and terms per topic distributions; that means a few topics per document and few terms per topic. The set of parameters is shown in Table 6.7.

The model uses an iterative sampling algorithm which improves log-likelihood with every pass over the data. The hyper-parameter of convergence was set for an earlier stopping to -1 with 1,000 iterations and the *n_check_convergence* hyper-parameter defining how often to calculate a score to check convergence to 50, which stops the model earlier if log-likelihood at iteration n is within 0.1% of the log-likelihood of iteration n-50.

Validation of the per-word perplexity metric was used to model a hyper-parameter tuning on a given dataset to estimate the optional number of topics. The perplexity is a measurement of how well a probability distribution predicts a sample - the lower perplexity, the better generalisation on unseen data. Other metrics were used for measuring semantic coherence. The intrinsic measure compares a term to the preceding and succeeding term; the ordered set is needed. It uses a pairwise score function, which is the empirical conditional log-probability with a smoothing count to avoid calculating the logarithm of zero. The extrinsic measure pairs every term with every other single term with PMI. The coherence score is then defined by both intrinsic and extrinsic measures since a mean divided of the pairwise word-similarity scores of the words in the topic. A good model generates coherent topics, that means topics with high coherence score.

Table 6.7: LDA model and hyper-parameters in R

```
## lda model ##
   lda_model = LDA$new(n_topics = 10,
                       doc_topic_prior = 0.1, topic_word_prior = 0.01)

    ## construct doc_topic dist ##
    doc_topic_distr = lda_model$fit_transform(x = dtm,
                                              n_iter = 1000,
                                              convergence_tol = 0.001,
                                              n_check_convergence = 50,
                                              progressbar = FALSE)
    ## check top words ##
    lda_model$get_top_words(n = 10, topic_number =
                            1:ncol(doc_topic_distr), lambda = 0.3)

    ## intrinsic and extrinsic coherence metrics ##
    tcm = create_tcm(it_tokens, vectorizer, skip_grams_window = 100L,
                     binary_cooccurence = T)
    diag(tcm) = attributes(tcm)$word_count
    intr_top = lda_model$get_top_words(n = 50, lambda = 0.3)

    ## coherence metric ##
    coherence(intr_top, tcm, n_doc_tcm=attr(pruned_vocab,
              "document_count")) %>% colMeans()

    ## perplexity metric ##
    perplexity(dtm,
               lda_model$topic_word_distribution,
               doc_topic_distr)
```

Furthermore, a hyper-parameter search with a genetic algorithm (Scrucca 2013) was performed to find a suitable LDA model. The search space is defined over dimensions of topics, document-topic distribution prior, and topic-word distribution prior. Objective (fitness) function is represented with the topic coherence metric. The optimisation setup for a genetic algorithm is printed in Table 6.8.

Table 6.8: Genetic algorithm hyper-parameter settings

```
GA settings:
Type                  =  real-valued
Population size       =  15
Number of generations =  100
Elitism               =  1
Crossover probability =  0.8
Mutation probability  =  0.1
Search domain =
      n_topics doc_topic_prior topic_word_prior
lower        6           0.001            0.001
upper       50           1.000            1.000
```

The first attempt aimed to model the complete dataset of lemmatised tokens without a selection of specific PoS tags and dependency relation tags or appraisal words removal. The topic can represent 1-3-grams. The created vocabulary was pruned to throw out very frequent (for example term "*zážitek"*) and very infrequent terms through adjustments of parameters of the proportion of documents which should contain the term, number of occurrences over all documents, number of documents containing the term and number of terms in the vocabulary. Table 6.9 demonstrates the size of vocabulary after pruning for a different selection of features for modelling.

Table 6.9: Size of vocabulary with different feature selections methods

	all tokens	**syntactic rules**	**without appraisal words**
vocabulary	201,025	60,718	24,490
pruned vocabulary	4,105	853	438

According to results gained by the genetic algorithm in Table 6.10 (the fitness function evaluation is depicted in Figure 6.4), ten topics were generated with new learned LDA with 100 iterations.

Table 6.10: Genetic algorithm results

```
GA results:
Iterations             = 100
Fitness function value = 0.912875
Solution =
     n_topics doc_topic_prior topic_word_prior
     9.020715        0.8993689       0.00640474
```

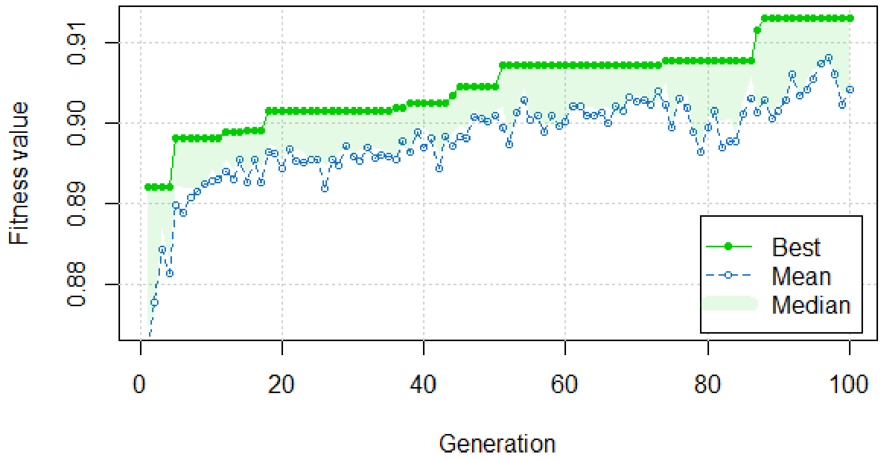


Figure 6.4: Topic coherence metric evaluation[56]

For a better exploration of topics and hyper-parameters, the R visualisation package LDAvis[57] (Figure 6.8) was utilised. The package provides an interactive tool for topic exploration. The top terms in the topic are sorted by a relevance metric which considers the frequency of the term in the corpus given a weight parameter lambda where 0 < lambda < 1 (for more information see (Sievert & Shirley 2014)).

However, the model has not achieved any understandable results, and perplexity was very high – 1020.714; therefore, further adjustments to feature selections were performed:

1) Selection of PoS tags and dependency relation tags based on defined syntactic rules

2) Exclusion of tokens representing the appraisal words from adjustment 1

3) Processing model on single products reviews with adjustments 1 and 2

The results with the adjustment 1 reduced perplexity significantly to 165.85 for ten topics, but the terms in topics still overlapped; thus, appraisal words were excluded from the vocabulary. The goal was to group the terms within the topic into aspect category. Figure 6.5 depicts perplexity for a different number of topics with different feature selection. It is seen

[56] The x-axis represents the number of iterations of the algorithm.
[57] Available at https://github.com/cpsievert/LDAvis.

that a higher number of topics lead to lower perplexity in all cases, and feature selection reduces perplexity significantly. Nevertheless, the goal was to reduce the number of topics; thus, domain knowledge was necessary to examine topics with LDAvis. After an examination of the performance measures, the author chose ten topics with perplexity 69.09. The topics were then examined by hierarchical clustering to find similar clusters. Figure 6.6 presents cluster dendrogram built on topic-word distribution inferred with adjustment 2. The top ten terms representing these ten topics are listed in Table 6.11.

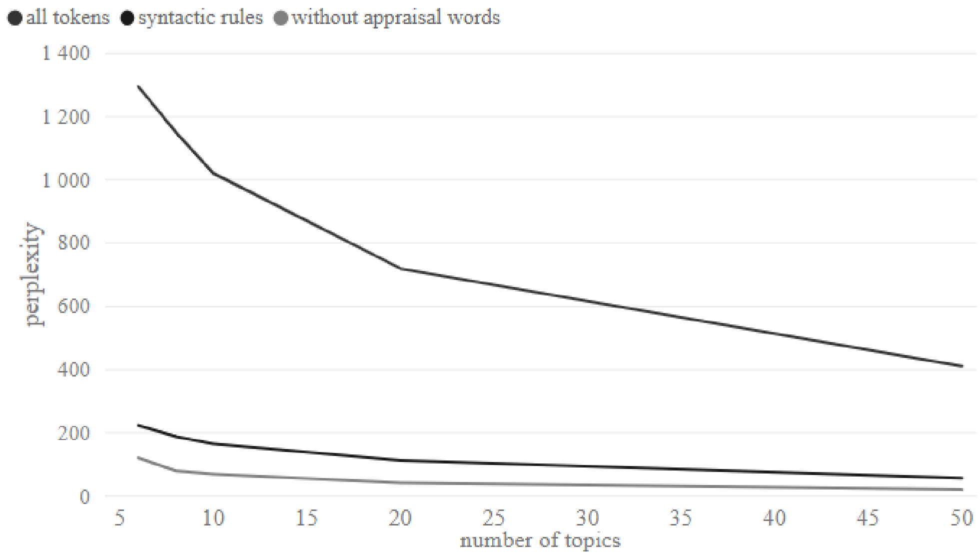


Figure 6.5: Perplexity measure comparing different feature selection

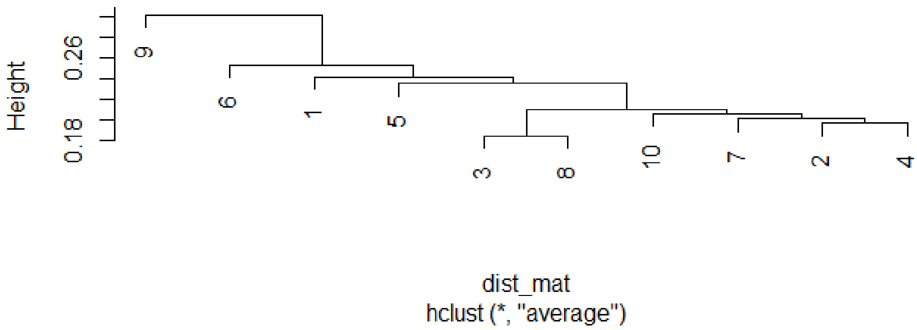


Figure 6.6: Cluster Dendrogram generated from topic-word distributions

Table 6.11: Top 10 terms for ten topics gained by WarpLDA based on adjustment 2

	topic 1	**topic 2**	**topic 3**	**topic 4**	**topic 5**
term 1	čokoláda	pilot	hra	cz	výběr
term 2	víno	km`kilometr	obsluha	oko	termín
term 3	ochutnávka	balón	služba	situace	konání
term 4	prezentace	domluva	okolí	profesionalita	lektor
term 5	rum	km`kilometr_hodina	loď	lektorka	zbraň
term 6	degustace	strach	jídlo	skok	prostředí_personál
term 7	výklad	let	hotel	zážitek_cz	místo_konání
term 8	pivo	domluva_termín	zámek	vyzkoušení	střelba
term 9	druh	most	restaurace	počasí	přístup_lektor
term 10	whisky	krajina	spokojenost	houpačka	konání_zážitek
	topic 6	**topic 7**	**topic 8**	**topic 9**	**topic 10**
term 1	jízda	ochota	ubytování	instruktor	výhrada
term 2	letiště	technika	masáž	přístup_instruktor	voda
term 3	minuta	očekávání	masérka	záznam	začátek
term 4	okruh	ochota_personál	parkování	video	organizace
term 5	sprint	trať	pobyt	kamera	vzduch
term 6	auto	bvp	stav	jednání	dotaz
term 7	vůz	výkon	zábava	zlepšení	instrukce
term 8	poskytovatel	instruktorka	praha	návrh	noha
term 9	dráha	areál	telefon	jachta	průběh
term 10	provoz	varianta	park	tunel	konec

The problem of the modelling over the whole dataset is that inferred topics incline to reflect the products (similar experiences) and not common features:

- Topic 1: tasting experiences
- Topic 2: flying experiences
- Topic 3: hotel stays
- Topic 4: skydiving
- Topic 5: shooting
- Topic 6: driving
- Topic 7: army experiences
- Topic 8: massages
- Topic 9: wind tunnel
- Topic 10: water experiences

Therefore, the model was performed over single products to gain topics regarding single products. Table 6.12 shows inferred topics for a product with the highest number of reviews (1,713) - "*wind tunnel*" based on processing with adjustment 1. The size of the vocabulary and pruned vocabulary with a different feature selection is depicted in Table 6.13.

Table 6.12: Inferred topics for the product “*wind tunnel*” with the WarpLDA after hyper-parameter tuning

Topic label	**Representative words**
personál	personál, přístup, přístup instruktora, instruktor, profesionální, příjemný, milý
čas	minuta, doba, volný, dobrý, termín, cena, krátký, rok
pocit	skvělý, úžasný, zkušenost, líbit, nový, pocit, super
organizace	recepce, tunel, létání, větrný, fotka, možnost

Table 6.13: Size of vocabulary for different feature selections for the product “wind tunnel”

	all tokens	**syntactic rules**	**without appraisal words**
vocabulary	26 743	5 723	1 977
pruned vocabulary	514	120	56

As the vocabulary is small in comparison to all products, the perplexity of LDA processed over all tokens is even better than with PoS selection (see Figure 6.7). After parameters tuning only four topics were determined to be relevant to this product. The distribution of topics as visualised by LDAvis is depicted in Figure 6.8. The highlighted topic represents *“personál” (“personnel”)* with its inferred terms.

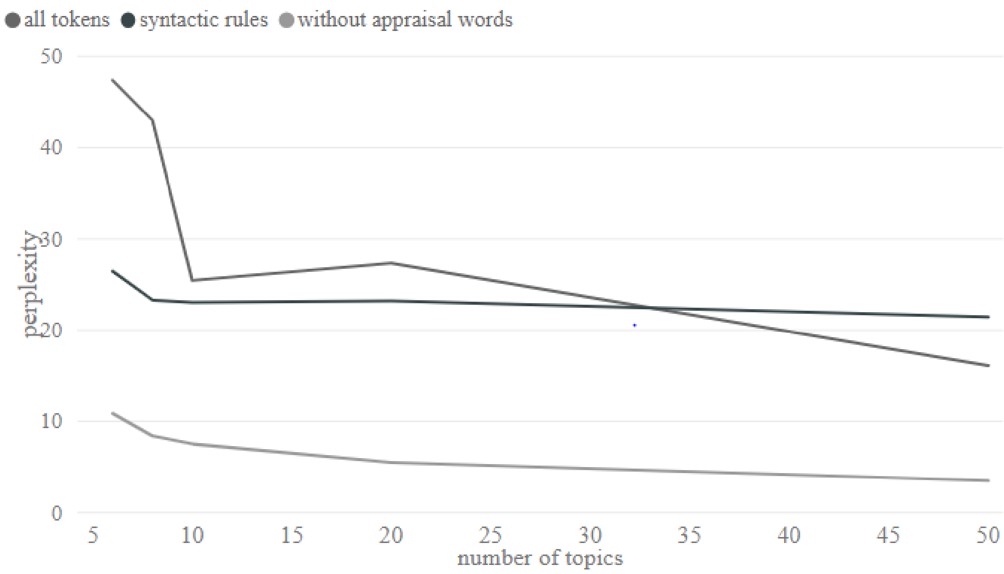


Figure 6.7: Perplexity measure comparing different feature selection for single product's reviews

After an in-depth examination of the results from LDA performed over all product categories with LDAvis tool, the following aspect categories were detected on the highest level of aggregation: *personnel*, *time*, *price*, *quality*, *feelings*, *organisation*, *weather*, *food*, *equipment*, *location*.

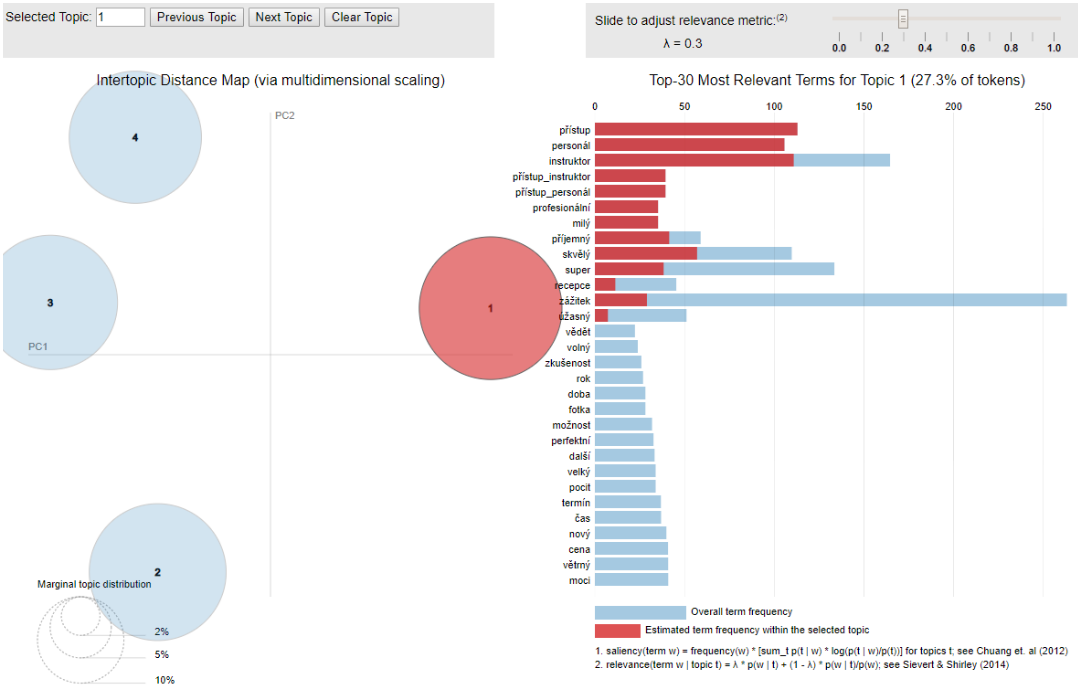


Figure 6.8: Results from LDAVis for the product "wind tunnel"[58]

6.2.5.3 Syntactic Rules for Aspects Detection

In the next phase, the syntactic rules to detect the aspects in every single sentence were implemented. The rules detected 51,108 aspects in the corpora. The method has some drawbacks. First, the same token can be detected as an aspect multiple times – as a unigram or as a part of the n-gram. For example, in the sentence:

Jízda nebyla až tolik adrenalinová, chtělo by přidat na rychlosti a na členitosti terénu.

(The ride wasn't very adrenaline-filled, increasing speed and incorporating more rugged terrain would be advisable)

following aspects were detected: *terén (terrain)*, *členitost (ruggedness)*, *rychlost (speed)*, *jízda (ride)*, *jízda na rychlosti* (ride on speed), *členitost terénu* (terrain ruggedness).

[58] The red colour of the bars indicates estimated term frequency within the selected topic. The blue colour indicates the overall term frequency. Circles represent single topics, their size set to be relative to the proportions of the topics across the total tokens in the corpus. When a single term is selected, the circles where the term is contained are highlighted with their sizes set to be proportional to the frequencies with which a given term is estimated to have been generated by the topics.

The second drawback is the inflexion of the tokens in n-grams which need to be converted to the right form. When the n-grams are built based on lemmas only, every single word in the n-gram is in the nominative form (e.g. *jízda na* ***rychlost****, členitost* ***terén***). Therefore, the author composed n-grams as a mixture of lemmas and tokens in an extracted form. When the token is not at the first place in the n-gram and has a relation dependency of a nominal modifier (nmod), adjectival modifier (amod), nominal subject (nsubj), object (obj) or noun after adposition, then the part of the n-gram is not a lemma, but the token in its extracted form (*jízda na* ***rychlosti****, členitost* ***terénu***). In many cases of bigrams where the first token is amod, the inflexion of the token and form of the lemma cause incorrect form of the word in bigram (e.g. the correct form of *ozářená krajina* is *ozářený krajina* in case of lemmas and *ozářenou krajinu* in case of tokens).

The comparison of detected aspects with manual annotation showed that automatic detection with the syntactic rules can extract more aspects (2,579 unique aspects from 5,883 detected aspects in 1,663 contributions), while annotators tended to aggregate aspects to categories (614 unique aspects from 3,602 detected aspects in 1,663 contributions).

The accuracy of rule-based aspect detection was calculated based on a labelled dataset of Czech aspect-level sentiment corpus (Steinberger et al. 2014) containing 2,149 sentences with 3,339 detected aspects. Due to the character of the task, only the true positive detection was taken into account. First, the issue of inflexion of detected terms in corpus had to be solved as not all terms were in their basic form, but in the form, as they appear in the text (with all the misspelling). Thus, author lemmatised all terms and corrected spelling. After correction of the terms, the rule-based approach correctly detected 98.06% of terms assigned to sentences. The closer examination showed that non-detected terms were mainly verbs or phrases containing more words than four-grams (e.g. phrase *plátek masa s pokrájenou zeleninou a čtvrtkami brambor (slice of meat with chopped vegetables and potato quarters)* the rule-based approach detected as three single aspects: *pokrájený zelenina (chopped vegetables)*, *plátek masa (slice of meat), čtvrtky brambor (potato quarters*). All terms were assigned to the category *jídlo (food).*

6.2.5.4 Emotion Detection

The Plutchik's eight discrete emotions were detected with the lexicon-based approach based on NRC Word-Emotion Association Lexicon (Mohammad & Turney 2010) and then improved with the Czech emotion detector tool.[59] First, the identical words appearing in NRC

[59] The tool for public use is available at https://www.alphai.cz/emotion/

lexicon were unified. The same words appear in the lexicon due to the translation as more English words are translated as the same Czech word (for example words *agreeable, pleasant, pleasurable* are all translated as *příjemný*).

The emotion detection was performed at the sentence-level. The algorithm was trained on 33,757 labelled sentences where 1,326 sentences belonged to the review dataset, and the rest was labelled by detector developers based on other datasets. The dataset was divided into the training data of 27,005 sentences and the rest 6,752 sentences represented the tested data.

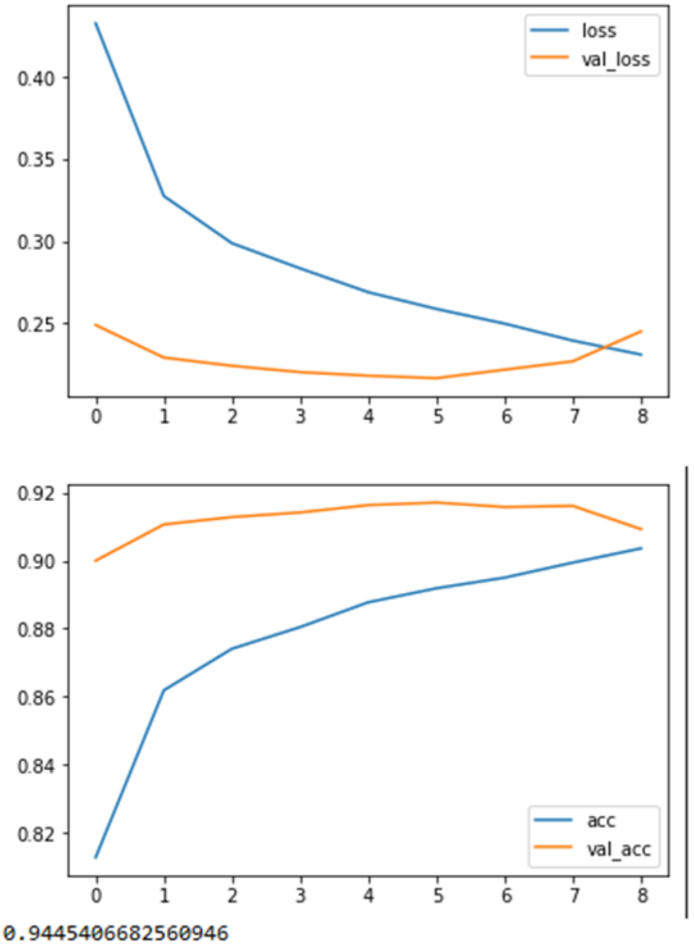


Figure 6.9: The accuracy of the deep learning system through the epochs[60]

The tool works based on deep learning. The best accuracy computed on the validation set (see val_acc in Figure 6.9) was achieved in the fifth epoch of the neural network. The

[60] The x-axis represents the epoch. Epoch refers to one cycle through the full training dataset before retraining. Results for epoch 9/9: 2s 87us/step - loss: 0.2310 - acc: 0.9036 - val_loss: 0.2451 - val_acc: 0.9092.

gained accuracy without the addition of an expert system in the form of the lexicons was 90% on the tested data and 94% on all data. The time of processing was 9 minutes.

The alternative measurement of the accuracy of the algorithm represented the test based on 40 questions evaluated by seven people as the company's internal experiment[61]. The loss was between 0.130 and 0.138; human annotators usually get the loss of 0.140 – 0.070 (see Figure 6.10). The loss of the algorithm in the fifth epoch was 0.130, after adding the expert system, the loss was 0.126 (the column Hybrid7 in Figure 6.10).

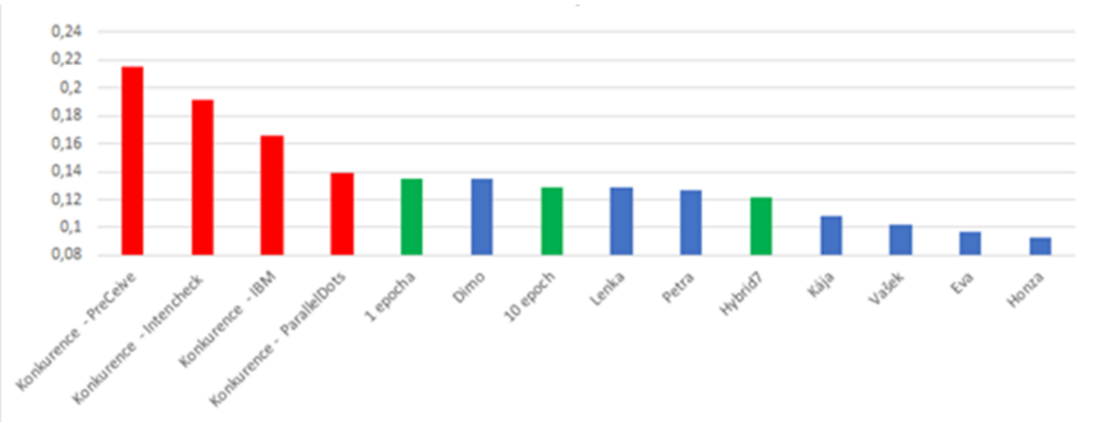


Figure 6.10: The loss of the different systems and annotators[62]

The algorithm was corect in assigning emotions to sentences with evaluative words carrying the sentiment as:

Dar jsem dostal k narozeninám, velmi spokojen.

(I received this gift for my birthday, very satisfied.)

- *Joy (very satisfied)*

Bál jsem se výšky

(I was afraid of the height.)

- *Fear (was afraid)*

Na korbě Hummeru jsem se opravdu bál, že spadnu.

(I was really afraid I would fall off the back of the Hummer.)

- *Fear (really afraid, fall)*

[61] This experiment falls under the confidential information of the company and cannot be published in this thesis.

[62] The red columns represent different tools of the competitors of the Alpha.ai; the blue columns represent human annotators; the green columns are results of the deep learning algorithm. The y-axis shows the loss.

The algorithm was wrong to assign emotions in sentences like:

Recepční byla trochu nervózní ze všeho.

(The receptionist was a little nervous about everything.)

- *The annotator assigned emotions of anger and disgust*
- *The algorithm assigned emotion of fear (probably joining nervousness with fear)*

Co se mi nelíbí je poměr ceny a doby trvání – asi 800 korun za 15 minut… ale stálo to za to.

(What I do not like is the price/duration ratio - about 800 crowns in 15 minutes ... but it was worth it.)

- *The annotator assigned emotions of joy and disgust*
- *The algorithm assigned emotion of slight anger (probably because of the phrase "do not like")*

Příliš mokrá voda ;-D

(Water too wet ;-D)

- *An annotator assigned emotions of joy and disgust*
- *The algorithm assigned emotion of slight sadness (did not understand the joke)*

The list of detected emotions by the neural network was limited to five – joy, fear, anger, sadness and disgust. The rest three, anticipation, trust and surprise, were additionally added according to NRC dictionary. A result is a number on a scale from 0 to 1 representing the strength of the emotion in the sentence.

6.2.5.5 Personality detection

Only one personality detection research based on psycholinguistic analysis has been conducted in the Czech language (Kučera et al. 2018) (see section 4.7). Since this analysis was carried out before the results of (Kučera et al. 2018) were published, the author of this thesis conducted an experiment following the study of Golbeck et al. (2011) based on Pennebaker's Linguistic Inquiry and Word Count (LIWC[63]) (Pennebaker et al. 2015). Moreover, in contrast to the laboratory condition of (Kučera et al. 2018) study where participants write long texts on a given topic, this thesis detects personality based on short customer reviews.

Since the LIWC dictionary works only based on English, the author translated all the reviews into English through Google Translator, which supports batch processing. The author

[63]Available at http://www.liwc.net.

is aware of the issue of losing the information and accuracy due to the translation. Therefore, the results from LIWC are also combined with the previously detected emotions and sentiment.

A total of 92 LIWC features were extracted from the customers' texts using the LIWC2015 (Pennebaker et al. 2015) software, which outputs features in many categories. Summary dimensions show structural features such as the total word count or the mean count of words per sentence. Other categories show relative frequencies of words found in each pre-defined category in the text: use of punctuation marks, function words (PoS), other grammar patterns or informal language; but also psychometric categories like perceptual processes (use of words such as see, feel), biological processes, drivers, time orientation, relativity, personal concerns, social references, cognitive process. The summary variables of analytical thinking, clout, authenticity, and emotional tone are standardised scores converted to percentiles made from various LIWC variables based on previous research. The complete output features information and their corpora are described in (Pennebaker et al. 2015).

Pennebaker and King (1999) and further Mairesse et al. (2007) conducted a Pearson's correlation analysis to asses individual features for modelling personality. They identified many linguistic features associated with each of the personality traits in the Five-Factor Model:

- **Extroversion** is positively correlated with positive emotions and total social references. LIWC categories showing the complexity of language are less frequent (articles, exclusive words, causal words).
- **Neuroticism** is positively correlated with negative emotions and negatively correlated with positive emotions. Neurotics use first-person singular pronouns.
- **Agreeableness** is positively correlated with positive emotions and negatively correlated with negative emotions. Moreover, agreeable people use fewer articles.
- **Conscientiousness** avoids negations, negative emotion words and words reflecting discrepancies (e.g., should and would).
- **Openness** to experience people prefer longer words and tentative expressions (e.g., perhaps and maybe), and reduce the usage of first-person singular pronouns and present tense forms.

With the translation of the texts to English, a substantial issue arises: the author could not take some features such as article or apostrophe (the significant determiners of extraversion) into account as these features do not appear in the Czech language. Qiu et al. (2017) confirm that some aspects of personality estimation based on the language are universal and valid in different cultural environments, while other aspects are culturally specific (see section 4.7). The author selected 35 features based on their universality, validity, and impact on personality. The author used only the LIWC features proven to have a significant impact on personality (at the p-value < .05 level) in previous research (Mairesse et al. 2007). A simple heuristic approach was chosen. Every personality is supposed to be defined by a set of features. Every feature except the word count can gain a score from 0 to 100 — features which are positively correlated to a personality aim to reach a high score. The negatively correlated features aim to reach a low score. The author summarised the score of features with a positive impact on specific personality and divided by the maximum possible score which features can gain. Features with negative impact were also summarised and divided by the maximum score, and the result was subtracted from the score gained from features with a positive impact. A result is a number indicating the weight for the given personality. This approach is heuristic and serves as an experiment as the author has no option to validate the correctness of the results at the time of the writing this thesis. This fact opens opportunities for future research.

The second approach used for personality detection was a simple categorisation into one of the five traits using the non-hierarchical clustering method k-means, where k = 5 since there are five personality traits. Based on the similarity of the results of all input features the method assigned one of the personality traits to every review contribution. K-means always converges at its local maximum and defines the total within-cluster variation as the sum of squared Euclidean distances between features and the corresponding centroid (see Feldman & Sanger 2007). The *kmeans()* function performed in R resulted in five clusters. After an examination of the results, every personality was assigned to one cluster according to the linguistic features defined by the previous research listed above: The largest cluster resulted in extroversion with 1,838 records. The smallest cluster (978 records) resulted in neuroticism. The validation of the correctness of the algorithm would require further research, for example, with a personality questionnaire submitted to every customer that this time was not allowed by stakeholders.

The advantage of the first approach is the possibility to refine the personality results based on new comments written by the same person. Every new comment is assigned with new weights which are averaged on the level of customer dimension. The clustering approach assigns personality category, which can change with every new comment.

6.2.6 Integration of the Results to the Unified Data Model[64]

After processing of the textual ETL containing the pre-processing and content analysis, the results of the modelling were loaded into the textual part of the multidimensional data model (according to the design in Figure 5.7) and then the analytical part (Figure 5.8) was commenced to fill the tables with available data. The analytical part is based on a previously built data warehouse, as mentioned in section 6.2.1. In comparison to the model of the analytical part in Figure 5.8, the data model of the company contains other tables specific to the business case described in section 6.1 Problem Investigation: tables *Reservation*, *Reservation_History* (the customer can re-book the reservation) and *Certificate* (see the data warehouse in Appendix C, Figure C.5).

A major problem that emerged during the integration was the missing unification of users. The operational system cannot recognise the same user and creates a new one for each transaction, reservation or inserted review. The unification of users is an essential step before processing any customer analytics – CLV prediction or RFM detection. The author thus implemented a matching transformation script based on emails, telephones and customer names. This process reduced the number of created users by 29%[65]. Moreover, the recognition if the person who purchased the product is also a consumer of the product was implemented. This recognition is vital for targeting the prospects to encourage them to purchase.

Further, the problem with detected aspects with missing appraisal words had to be solved. The text in columns *Pros* and *Cons* represents answers to the question “What I (did not) like at the experience” does not always contain appraisal words, but only listed aspects. In that case, the sentiment is assigned as +1, if the aspect is listed in the *Pros* column, and -1 if the aspect is listed in the *Cons* column.

6.2.6.1 Customer Lifetime Value and RFM

The transactional data were used for calculation of the Customer Lifetime Value (CLV) and detection of RFM. These measures were further integrated with the mined textual information. CLV was predicted with the use of probabilistic models (also called “buy-till-you-die” - BTYD) which were proven suitable for predicting CLV in a non-contractual environment as described in author’s articles (Jašek, Vraná, Šperková et al. 2018, 2019a, 2019b). These articles comparing different CLV models on ten e-commerce datasets were successfully adopted by the academic community and implemented in practice. The implementation of the probabilistic was performed with the R package *BTYD* (Dziurzynski et

[64] This section corresponds to the Deployment phase of CRISP-DM methodology.
[65] 112,483 customers were reduced to 80,020.

al., 2015) and *BTYDplus* (Platzer, 2016). Table 6.14 presents the results of six chosen models for the company's dataset: Pareto/NBD, Beta-geometric/NBD (BG/NBD), Beta-geometric/NBD with Fixed Regularity (BG/CNBD-k), Modified Beta-geometric/NBD (MBG/CNBD) and Modified Beta-geometric/NBD with Fixed Regularity (MBG/CNBD-k). For a further description of the models see author's articles (Jašek, Vraná, Šperková et al. 2018, 2019a, 2019b) as the explanation is not the aim of this thesis.

The input data come from the *Order* table containing 64,565 orders (attribute *order_id*) from 50,747 customers (*customer_id*) aggregated on a weekly level of each customer's purchases where attribute *week_number* corresponds to the dataset data range counting from number 1. A specific week is also characterised by *monday_date*. *Profit* represents the value of the order the customer paid, excluding all discounts, the delivery amount and VAT. As several purchases could be made during one week, *avg_purchase_day* demonstrates the average of individual transaction weekdays (1 = Monday). *Count_transactions* attribute counts the number of orders made in a given week. The data contain a history of more than seven years from the beginning of 2012 to the middle of 2019 with a profit of almost 144 million Czech crowns.

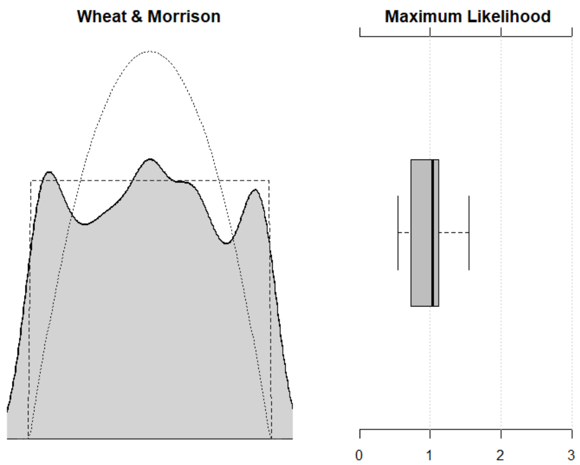


Figure 6.11: Regularity estimation

The models belong to the 'maximum likelihood models' category as they can be efficiently estimated via means of maximum likelihood estimation (MLE). The used models are capable of leveraging regularity within transaction timings for the improvement of the forecast accuracy. Estimation is made assuming the same degree of regularity in the event timings across all customers (Wheat & Morrison 1990). A return value of close to 1 supports the assumption of exponentially distributed inter-transaction times, whereas values significantly larger than 1 reveal the presence of regularity. The graphical representation of the estimations is depicted in Figure 6.11.

The training period represents the whole customer's history, and the CLV was predicted for one year (52 weeks). First, to compare the results of different models, the last year of data history was used as a testing period. For more information about the process of the modelling, see the author's article in (Jašek, Vraná, Šperková et al. 2019b). Figure 6.12 shows the graphical representation of the results of the modelling with Pareto/NBD model based on transactions; the results of all applied models on aggregated customer base level are then listed in Table 6.14. As Pareto/NBD offered the best results, the model was used for a prediction of the next one-year period on customer level and the results integrated to the Customer Experience data model. The results are stored in the analytical stage in the *CLV* table where every customer represents one record in the table and predictions are stored in columns together with the results from other models for comparison (one model result represents two columns – one for a profit prediction, one for transactions prediction). The stakeholder can then choose the model. In default, Pareto/NBD is selected. In the future, the results from text analytics (satisfaction) are intended to input the models for modelling the CLV.

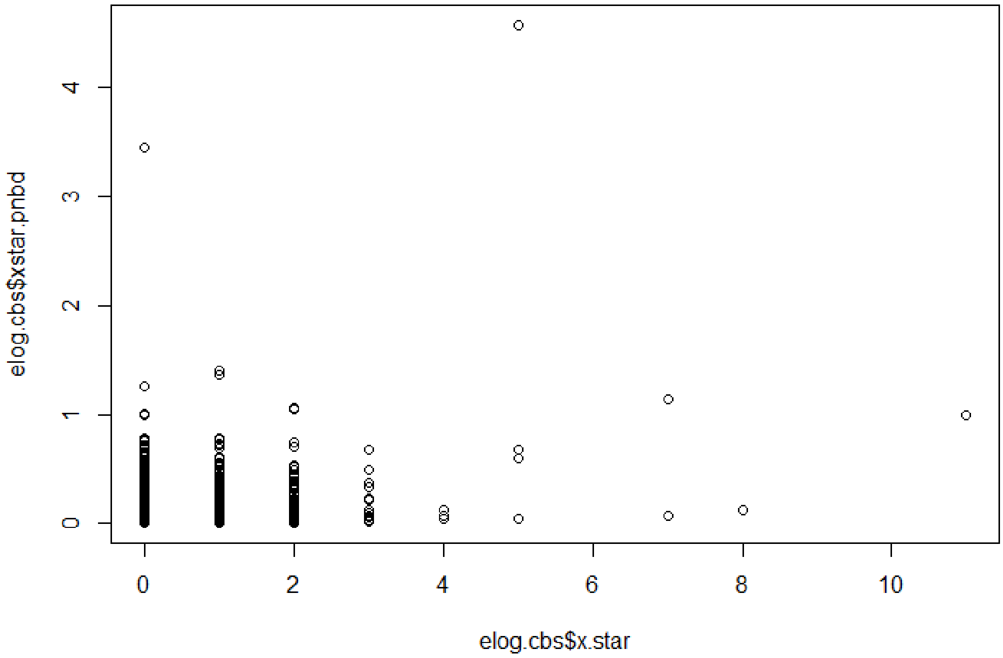


Figure 6.12: Boxplot comparing the prediction of the number of transactions with the actual values at the aggregated level for the Pareto/NBD model[66]

[66] The x-axis represents the actual number of transactions, the y-axis represents the prediction with the Pareto/NBD model.

Table 6.14: Results of the CLV models

Model	Number of transactions	Profit
Actuals	2,259	5,274,357
Pareto/NBD	2,066	4,846,137
BG/NBD	1,910	4,489,715
BG/CNBD-k	1,910	4,489,715
MBG/NBD	1,880	4,418,268
MBG/CNBD-k	1,880	4,418,268

The RFM segments were refined according to stakeholders' needs – stakeholders defined their own nine RFM segments concurring to results of frequency, monetary and recency value sorted into 125 bins with scores 1 – 5 for each value. The RFM was performed with the use of R package 'rfm' (Hebbali 2019). The input data for the RFM analysis was the table *Order* with attributes *customer_id, order_id*, *profit* and *date*, just like in the case of CLV. The results are then stored in the analytical stage in the *RFM* table. Visualisation in Figure 6.13 shows segments based on stakeholders' data with the prevailing segment of potentially loyal customers (31.5%), following new customers (15.5%) and hibernating customers (14.3%) as visualised in the report.

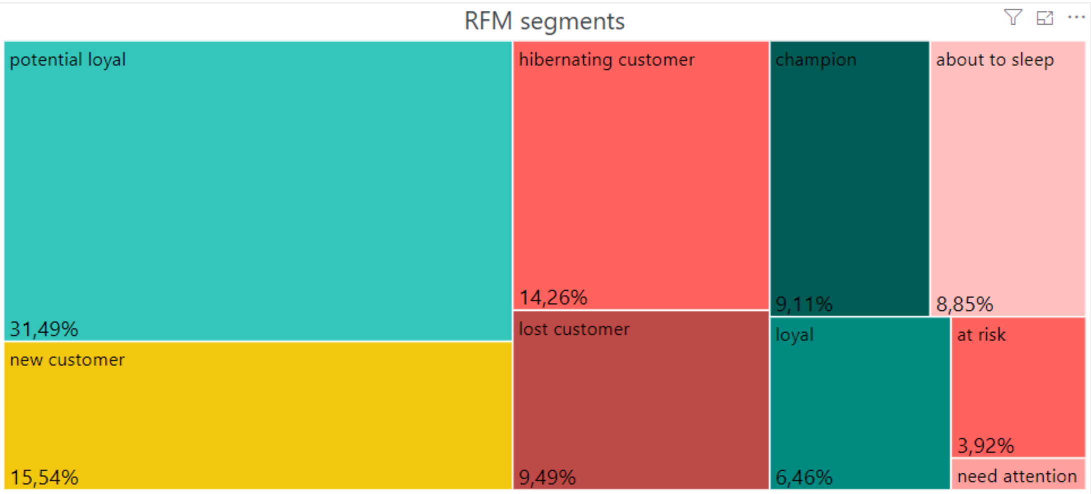


Figure 6.13: RFM segments in stakeholders' company

6.2.6.2 Reports and Dashboards Design

The author designed a package of interactive reports that can be divided into company perspective, product perspective and customer perspective reports based on the level of aggregation and applied dimensions. The reports can be used daily; some of them make more sense on a weekly or monthly basis. All reporting was built with the Business Intelligence software Power BI by Microsoft.

The company perspective presents the highest level of customer aggregation. Inside the reports, one can find visualisations of customer cohorts, month seasonality line-charts, Pareto charts and trends according to the customer segments. The reports are interactive and enable to drill-down and drill-trough to other levels or dimensions. Figure 6.14 and Figure 6.15 present examples of two company perspective dashboards. The first dashboard is a visualisation of the results of RFM analysis which is based on customers' transactions. The visualisations change according to the chosen segment and provide detailed information. Stakeholders can refine the period they want to see (in weeks, months, years or specific dates) and with the slicer selection if the customer is also a consumer of the product (this information is recognised from the reservations). In the left column, there are overall metrics of profit, number of customers (buyers), average order discount and average order profit. The boxplots compare the relationships between the recency, frequency and monetary values of customers. The column charts show the number of customers according to their profits and transactions. The stacked chart at the bottom of the layout shows the percentage of profit according to the acquisition year, and the line chart presents the ratio of profit of repeat customers (customers who have made a purchase more than once). The cohort on the left bottom contains a percentage of customers who bought something during the next period of one year.

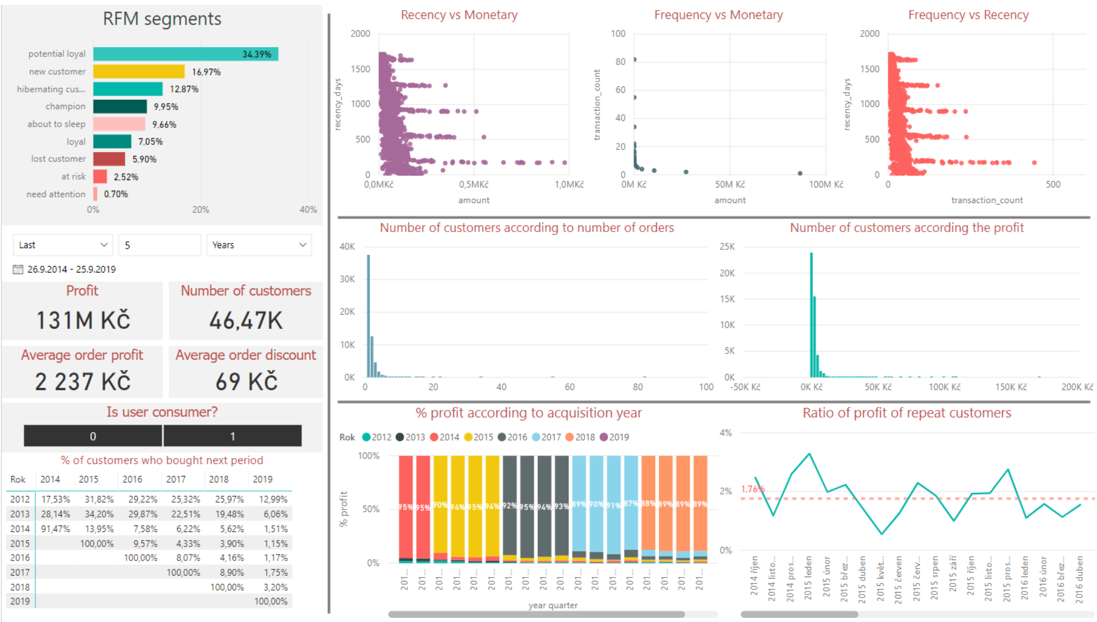


Figure 6.14: Company perspective dashboard: the RFM view

Furthermore, the second dashboard represents the integration of structured transactional data with information gained with text analytics and is focused on customer reviews. The input is the slicer of RFM results which now serve now as a dimension, and the state in the customer journey. Prospect is a person who participates in the experience and writes a review but has not bought any product yet. All visualisations are interactive and can influence each other. The line charts illustrate the sentiment and emotions in time. Recommendation score also serves as a slicer (as customers can choose among four selections on the rating scale). Thus, stakeholders may analyse the sentiment, emotions and personality for those with the lowest score. The table in the middle displays the individual aspects detected in the comments with the sentiment, number of users who used that aspect, number of reviews and number of products (experiences). The combined line and yellow column chart represent the number of reservations with the number of reviews (more reviews can be written on one reservation because more people can participate in the experience). The radar chart indicates the strength of each of the five personality traits. The emotions that prevail in each segment can be found in the doughnut chart (fear is prevailing emotion as many of the offered products are adrenaline experiences). The small column charts and pie chart in the right segment represent newsletter subscription, gender, and whether a customer represents a company or a person. The stakeholders can download underlying data with a right-click on the element at the dashboard. For instance, after specific filtering on a dashboard, they can download related customers that match the filtering (for example, loyal customers with prevailing emotion of joy).

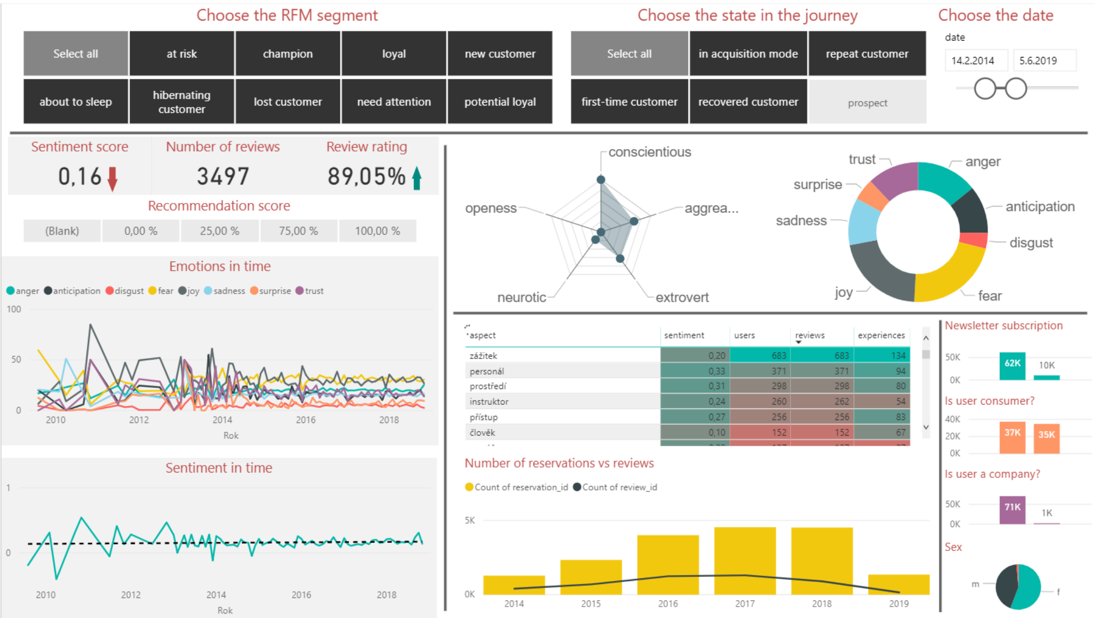


Figure 6.15: Company perspective dashboard: customer reviews

It was discovered that customers are generally not neurotics. In the segment of lost customers, neuroticism has increased together with the reduced sentiment. This observation may indicate that the offer of products is not for neurotics. One type of reports allows stakeholders to refine sentiment score together with the chosen emotion and list the customers who match the selection. In the report depicted in Figure 6.16, the stakeholder set sentiment score to negative numbers and emotion of anticipation to high values (the idea eas to detect customers with unfulfilled expectation). The result is a list of customers and their corresponding RFM segment. The personality column chart can be filtered if a single customer is clicked.

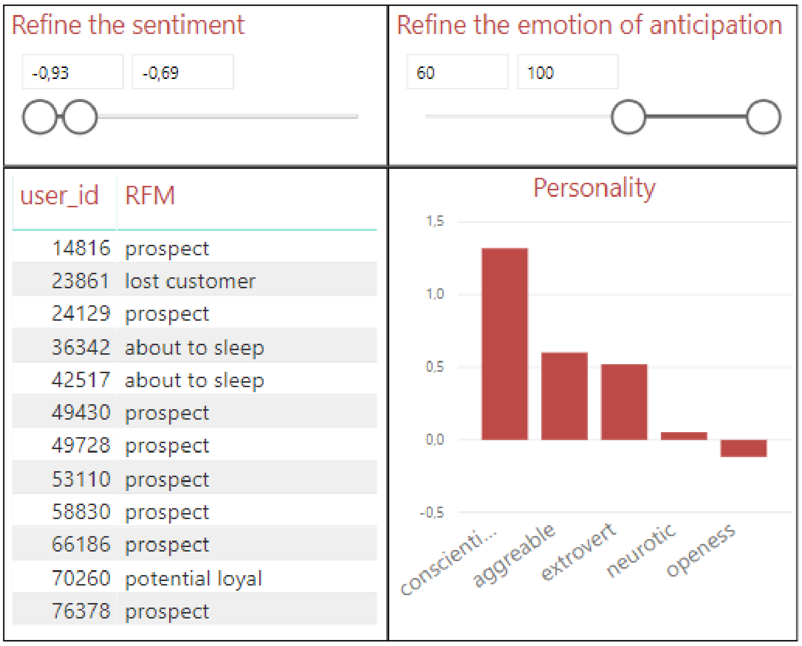


Figure 6.16: Report with the selection of customers matching the slicers refinement

The report in Figure 6.17 demonstrates the relationship of the information from textual data with the predictions based on transactional data. The bubble chart presents the correlation of the predicted CLV with the customer's average sentiment. The input data contained customers who made a purchase in the last year and made a total of more than two purchases and wrote at least on review. In the report is possible to observe, that the prevailing sentiment is mostly positive. However, customers with a lower average sentiment do not have a prediction of CLV more than 400 Czech crowns.

Additionally, monitoring of the impact of different channels in marketing activities belongs to other company-perspective reports. Next to financial indicators stakeholders find examples of monitored metrics impressions, clicks, post engagements, conversions, likes on Facebook, watch time of videos, number of public comments, number of shared posts and many others. These metrics, when assessed, indicate the involvement level and referral value of the customer basis. The prevailing sentiment, emotions and personality will also be monitored in the future by analysing public comments. Another important company perspective report is monitoring the behaviour of customers at the company's websites (visits, bounce rates, conversions) where information is extracted from the web analytics platform Google Analytics. The aim of the next iterations of the treatment design is the mapping of a single customer through these systems to recognise measured values at the customer level.

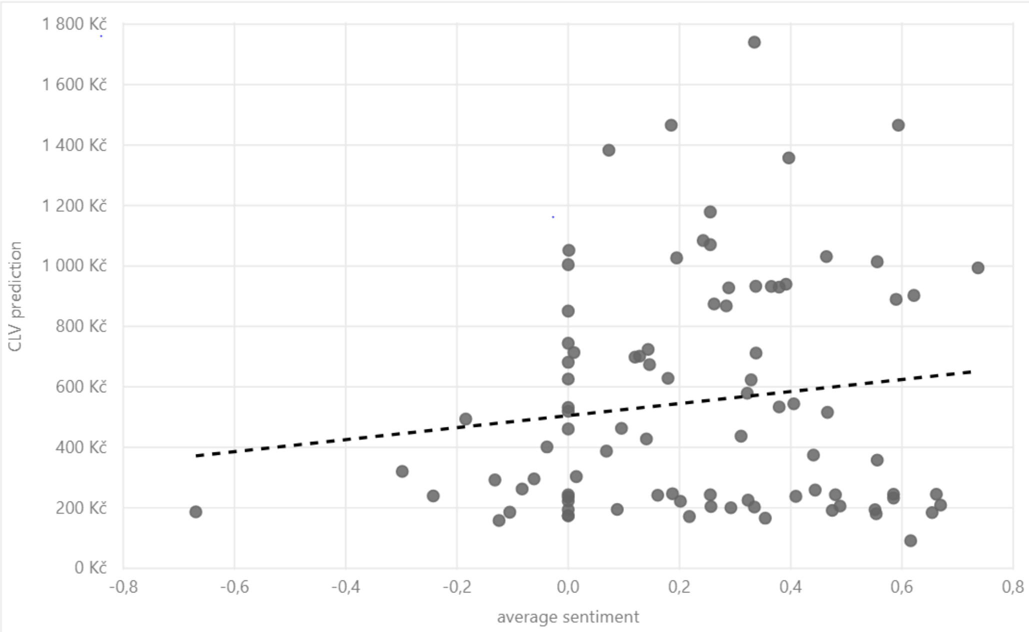


Figure 6.17: Correlation of the average sentiment with the CLV prediction

The product perspective reports contain information from the point of view of the product. Figure 6.18 represents an example of the dashboard where stakeholders can filter specific experience (product) or category (in the example flight experiences are filtered). The grey areas then calculate the metrics according to products filtered. The reviewability presents the ratio of purchased products reviewed. Notice that the sentiment score is significantly lower than the review rating. That confirms the assumption already mentioned in Chapter 2 that a reviewer can give a high rating, but at the same time write a comment evaluating the negative aspects of the product. These aspects are listed in the tables at the bottom of the layout where the stakeholder can also filter in what type of comment the aspect was mentioned and how many reviewers mentioned that aspect. The aspects are also divided according to a polarity to negative and positive. The horizontal column charts show the scale rating of satisfaction dimensions of value/price, location, term and personnel. In Figure 6.19, the scale rating of these four dimensions is compared to the sentiment of the same dimensions detected in the text as aspect categories. In the table, it is observable that the scale rating does not correspond to the detected sentiment – this finding confirms what has been found in earlier research (see section 2.3). Moreover, sentiment and emotions are possible to monitor in time.

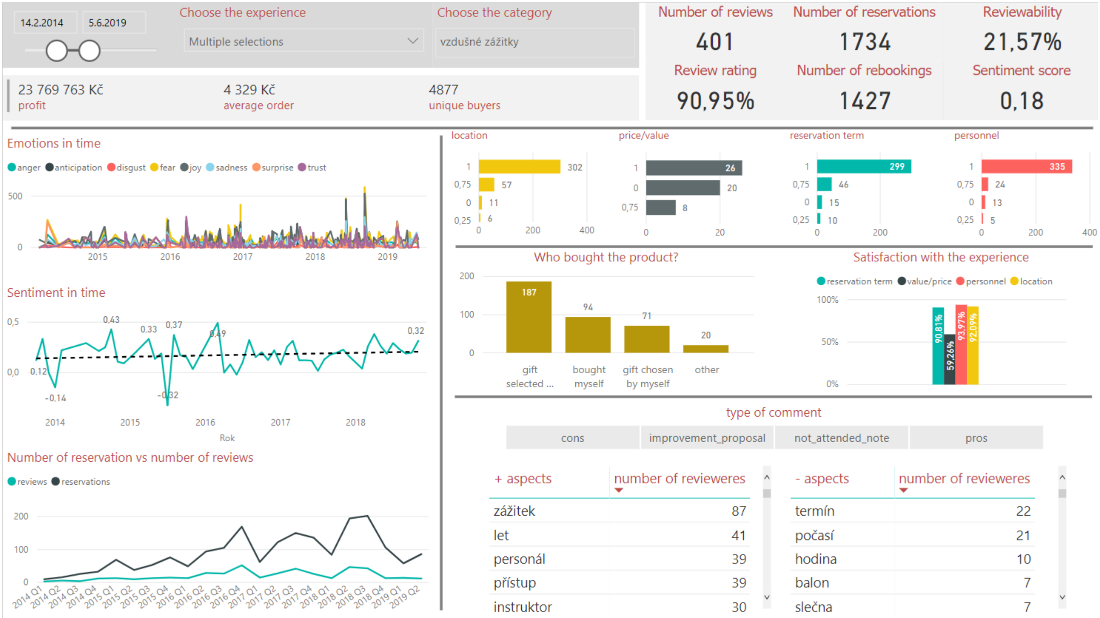


Figure 6.18: Product perspective dashboard

sentiment					scale rating				
category	cena	místo	personál	termín	category	cena	místo	personál	termín
Akrobatické lety		-0,50	1,00	-0,50	Akrobatické lety	75,00 %	100 %	100 %	100 %
Bali masáže	-0,67	0,00	0,80	-1,00	Bali masáže	40,00 %	94 %	86 %	97 %
Bungee skoky	0,00	0,06	0,51	0,42	Bungee skoky	38,89 %	89 %	87 %	88 %
Degustace	-0,11	0,14	0,68	-0,35	Degustace	43,75 %	80 %	91 %	73 %
Horolezectví		0,13	0,86	-0,33	Horolezectví	81,25 %	86 %	90 %	60 %
Kurzy vaření	0,50	-0,67	0,72	-0,33	Kurzy vaření	83,33 %	89 %	93 %	71 %
Lety balónem	-1,00	0,09	0,50	-0,38	Lety balónem	25,00 %	96 %	92 %	84 %
Paintballové střílení	0,33	0,33	0,70		Paintballové střílení	0,00 %	95 %	97 %	98 %
Pilotování		1,00	0,70	0,00	Pilotování	75,00 %	83 %	81 %	83 %
Pivní lázně	0,00	0,50	0,69	-0,33	Pivní lázně	100,00 %	96 %	88 %	89 %
Proměny	0,00		0,00		Proměny	75,00 %	88 %	63 %	100 %
Segway		0,40	0,80		Segway	50,00 %	81 %	84 %	88 %
Škola smyku	-0,50	1,00	0,56	-1,00	Škola smyku	100,00 %	90 %	85 %	88 %
Supersporty	-0,46	-0,28	0,52	0,00	Supersporty	6,25 %	69 %	77 %	81 %
Tantra masáže		1,00	0,50		Tantra masáže		100 %	100 %	92 %
Terénní vozy	-0,50	0,50	0,60	-0,36	Terénní vozy	0,00 %	87 %	88 %	80 %
Thajské masáže	0,00	-0,14	0,81	0,23	Thajské masáže	71,15 %	93 %	92 %	94 %
Vodní zážitky	-0,19	0,32	0,77	-0,19	Vodní zážitky	36,76 %	89 %	92 %	87 %
Vyhlídkové lety	0,50	0,33	0,81	0,00	Vyhlídkové lety	41,67 %	88 %	92 %	89 %
Zážitky na sněhu		0,00	1,00	-1,00	Zážitky na sněhu		90 %	80 %	95 %
Total	**-0,19**	**0,10**	**0,68**	**-0,22**	**Total**	**45,16 %**	**87 %**	**89 %**	**84 %**

Figure 6.19: Comparison of the scale rating of satisfaction dimensions to the detected sentiment[67]

The customer perspective reports represent the lowest level of aggregation, enabling the view of a single customer. The example of the dashboard in Figure 6.21 allows to choose a single customer, and the grey fields then display his state in the journey, RFM segment and other Customer Experience metrics like involvement score, referral value or sentiment score. The average order discounts detect if a customer is applicable for discounts. The flag which differentiates if the person is only a customer (buyer) or also a consumer of the product is on

[67] Translation: cena = value/price, místo = location, personál = personnel, termín = term

the right top of the layout. The state in the journey can be drilled through to see the history of the customer's states (Figure 6.20). The acquisition period for new-coming customers was set to three months (91 days).

date	state-in-the-journey
22.01.2014	first-time customer
15.05.2014	repeat customer
14.10.2014	repeat customer
24.02.2015	repeat customer
14.05.2015	repeat customer
19.05.2017	recovered customer

Figure 6.20: Report: Customer state in the journey changes

Among other metrics belong CLV predictions for the next period. The dashboard is a combination of information from textual and structured data. The line chart shows sentiment changes in time; the bottom left box then the customer's state of mind – personality and emotions. The mentioned aspects are listed in tables divided into positive and negative with the assigned sentiment. At the right part of the dashboards are also displayed full-texts of comments if more in-depth analysis is needed.

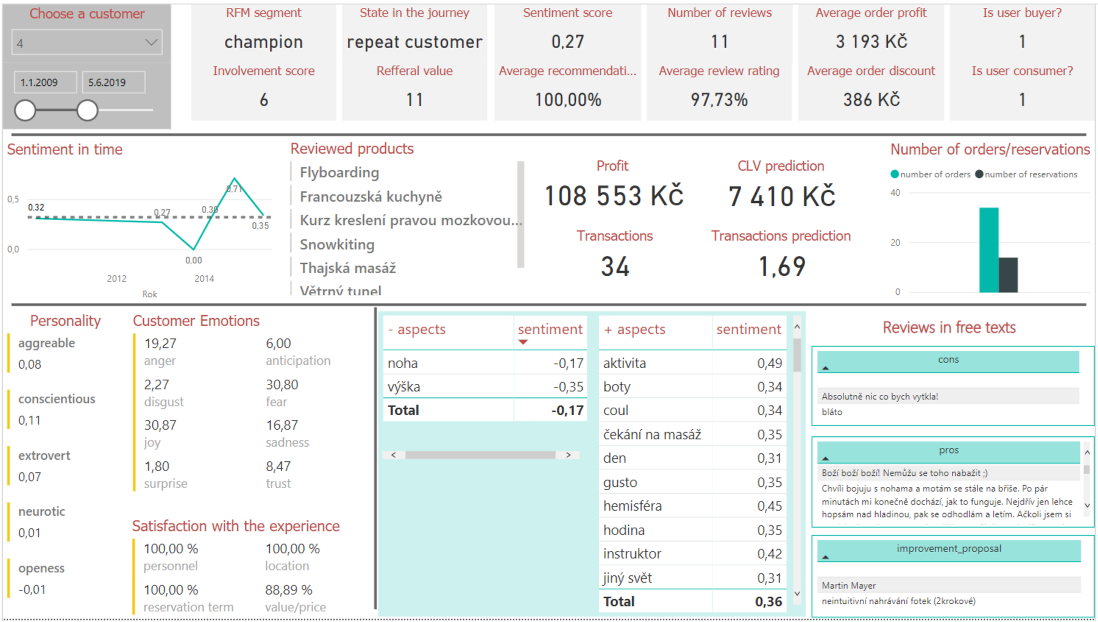


Figure 6.21: Customer perspective dashboard: single customer view

6.2.6.3 Proposed Marketing Activities

Managing Customer Experience Measurement has a direct impact on marketing activities. The activities can be targeted based on customer segmentation according to the results of the metrics in different dimensions. The author proposed the following activities related to stakeholders' goals based on the information from textual data.

- Prioritisation in treating customers based on their experience. Identification of the sentiment and satisfaction of the communication to handle priority customers' requests. For example, if a customer has high RFM and shows negative sentiment, it may be more convenient to prioritise them when handling the issue.
- Prioritisation of the touchpoints with which customers have a good experience.
- Identification of recurring customers' issues with the products based on detected aspects. Marketing nudge can be offered to a segment of customers which experienced a similar issue with certain product as compensation.
- The recommendation of the products based on the positive evaluation by other consumers of the products to customers or potential customers with similar experienced emotions or personality type.
- Customer churn prediction. Expressed emotions and sentiment together with purchase behaviour can predict the customer churn. The definition of the typical sequence of events before the customer churn enables to create an activity to prevent the churn of customers who are already in the path-of-churn.
- Prediction, how a targeted offer will impact satisfaction and potential revenue.
- Product forecasting. Determination, if the customer satisfaction corresponds with their purchase behaviour and correlation of the development of sales with the overall mood of VoC further serves for forecasting which product or service can be more profitable than other products or services. This knowledge is a base for cross-selling and up-selling activities.
- Correlation of the development of new customers with the overall mood of VoC. A decision which strategy to focus on – acquiring new customers or retention and in which proportion.
- Monitoring the referral value of the customer and data from public sites. Targeting to acquaintances of customers who speak positively about the product. Reallocation of marketing costs based on customer reactions to the campaigns.
- Monitoring the customer's overall personality. A combination of emotions characterises a customer's overall personality. This result can be used to sell a customer a specific product or services. The concrete examples for the stakeholders' company are:
    - Adjusting sales messages and promotions to resonate with customer's emotions. The customer perspective enables replacing mass marketing

conducted on aggregated data with the customer-oriented well-targeted approach.

- Offering extra insurance to customers with a particular personality type. For example, a negative person could be willing to buy extra insurance for the chosen experience. Alternatively, marketers can adjust their sales messages and promotions, which resonate with the customer's personality.

6.3 Design Validation

In the engineering cycle (Wieringa 2014), when treatment is designed, it is validated before it is implemented. This section assesses whether the designed treatment satisfies stakeholders' goals, and what would happen if the treatment was utilised in the real world. According to (Wieringa & Morali 2012), four knowledge questions must be answered before the treatment implementation. These questions were answered with the stakeholders based on the designed artefact.

1) *Expected effects: What will be the effects of the artefact in a problem context?*
2) *Expected value: How well will these effects satisfy the requirements?*
3) *Trade-offs: How does this treatment perform compared to other possible treatments?*
4) *Sensitivity: Would the treatment still be effective and useful if the problem changes?*

The artefact's primary **expected effect** in a problem context will be mitigation of the stated barriers from section 3.3.3. It is believed that the proposed Customer Experience data model would have a positive impact on the ability to perform Customer Experience Measurement which is now evaluated based on fragmented reports delivered from third-party consultants based on a measurement of customer interactions with different marketing channels at an aggregated level of the entire customer base and transactional data. The current stakeholders' report which monitors customer reviews contains only quantitative metrics of the number of reviews and their average rating in years for product categories. The textual comments are not analysed and manually read by employees instead. It is believed that the automatic analysis of textual data will contribute to the effective monitoring of reviews and new insights will be found in connection with the data from other sources. Also, it will be possible to measure experience in a lower granularity of customer segments or even at the level of individual customers. All the employees will have to learn to use the available technology to manage and monitor reports on a daily level.

The stakeholders confirm that the artefact can deliver specified goals *SG1* and *SG2* after implementation. The **expected value** defines how well the artefact satisfies its criteria. All criteria defined according to stakeholders' goals in section 6.2 were fulfilled.

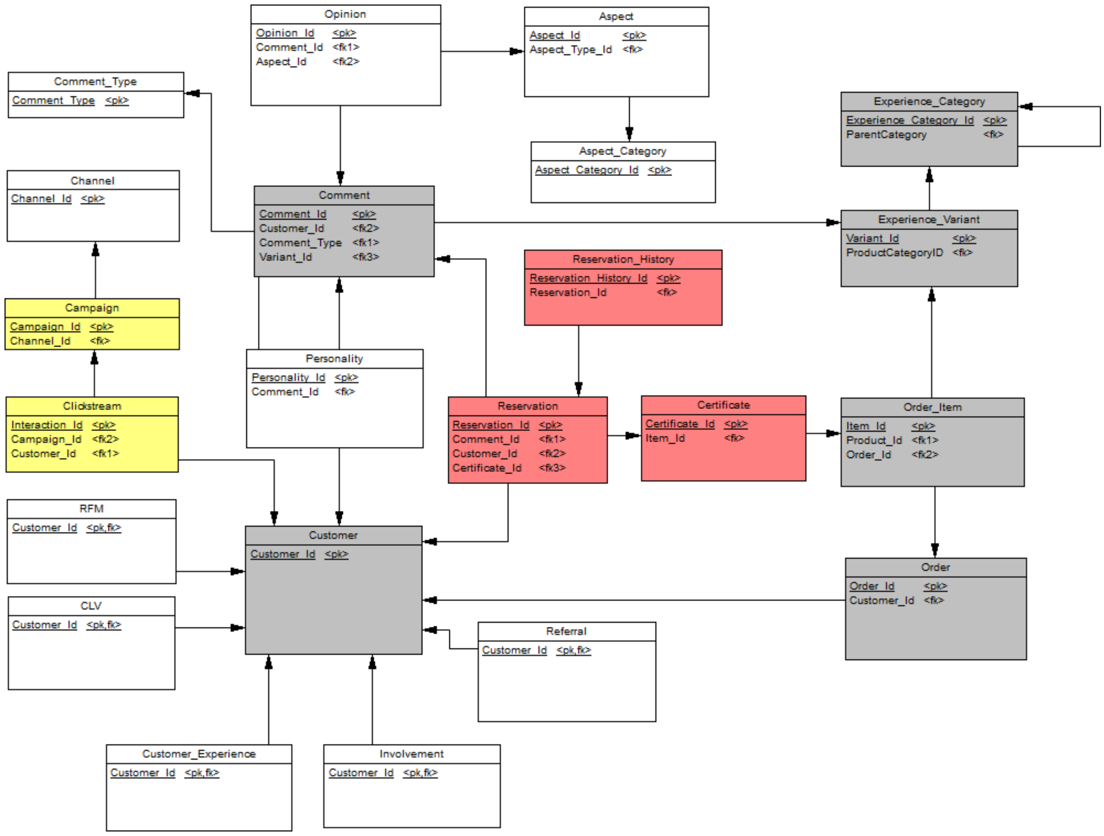


Figure 6.22: The analytical stage of the stakeholders' company

The criterium 1) "*To implement the textual data stage to existing BI data model and fill it with data based on the information gained from customers reviews*" was fulfilled by utilised methods in 6.2.5 Modelling and Results with the satisfaction of the requirements for text analytics methods to mine Customer Experience elements stated in section 4.2. All the elements of Customer Experience were determined and information stored in the data model. The simplified diagram of the model showing relations between tables and their keys represents Figure 6.22. The grey and red tables come from the internal data warehouse (see Appendix C, Figure C.5). The *Experience_Variant* table represents the *Product*, *Experience_Category* represents the *Product_Category* according to the data model designed in the artefact (Figure 5.8). The red tables *Reservation*, *Reservation_History* and *Certificate* are specific to the business case of the stakeholders. The yellow tables *Clickstream* and *Campaign* contain data from Google Analytics. The white tables were added by the author to load the information from the text analytics methods, data mining based on transactional data and other analytical results. Other tables from the stakeholders' BI data model that do not directly relate to the author's tables were intentionally omitted together with the date dimension and historical tables for the model readability.

Table 6.15: Metrics validation

Metric/Indicator	**Possible to measure in treatment implementation?**
Customer Effort Score (CES)	No – no data available
Customer Satisfaction Score	Yes – data from table Reviews
Discrete Emotion	Yes – data from table Reviews
Emotional Value	Yes – data from table Reviews
First Response Time	No – no data available
Involvement level	Yes – data from table Reviews / social networks
Net Promoter Score (NPS)	Yes – data from column Recommendation in table Reviews
Number of cancellations	Yes – from transactional data – table Order and Reservation
Number of complaints	Yes – data from table Reviews
Number of compliments	Yes – data from table Reviews
Number of public comments	Yes – data from table Reviews, social networks
Number of requirements	Yes – from table Reservation (requirements on re-booking)
Number of returns	Yes – from transactional data
Number of suggestions	Yes – data from table Reviews
Personality	Yes – data from table Reviews
Problem Resolution Time	No – no data available
Recency, Frequency, Monetary (RFM)	Yes – from transactional data
Referral Value	Yes – data from table Reviews
Review Score	Yes – data from table Reviews
Sentiment	Yes – data from table Reviews
Share-of-Wallet	No – no data available
Value of Knowledge	No – no data available

The criterium 2) "*To expand the textual stage to the analytical stage to gain the complete Customer Experience data model to monitor the Customer Experience measures according to Table 5.1: Metrics and Indicators in Customer Experience* Measurement" was assessed based on available data in stakeholders' company. Table 6.15 lists the metrics of the designed artefact from section 5.3 with the information if they can be measured in treatment implementation. Five metrics are not viable for implementation due to unavailability of data. All others were parts of the Customer Experience Measurement reports in designed treatment. Due to the experimental character of personality detection, this metric will not be part of the Customer Experience Measurement in treatment implementation.

Second, it was validated if the Customer Experience data model can fulfil the analysis requirements for the model stated in section 5.4., and if it is possible to implement these analyses in the next phase (Table 6.16). The validation was performed with the sample queries to the designed data model. The queries reflected stakeholders' questions regarding the analysis requirements[68] and the answers were presented in reports. All analysis requirements were satisfied as all type of analysis were used in reporting design.

The criterium 3) "*To propose reports/dashboards based on the Customer Experience metrics and indicators from Table 4 with using dimensions from Table 5.2"* was satisfied with the set of reports defined with available data for metrics and dimensions. The reports were divided into a company, product and customer perspective based on the level of aggregation that the stakeholder wants to use. Some reports were too complicated for the stakeholders to understand; thus, some simplification is needed during the implementation.

Table 6.16: Fulfilment of the analysis requirements for the Customer Experience data model

Analysis Requirement	Possible to perform with the designed metrics and the data model?
Campaign analysis	Yes – the company uses many systems for campaign performance monitoring. Only at the customer aggregate level.
Customer behaviour	Yes – based on transactional data and textual data.
Customer expectations and perceptions	Yes – monitoring of the sentiment and rating of quality dimensions together with mentioned aspects in the textual data.
Customer loyalty	Yes – the loyalty results from the satisfaction and purchase behaviour, which results in the state in the journey.
Customer personality and emotions	Yes – after training the text analytics models with satisfying accuracy.
Customer profitability	Yes – based on transactional data.
Customer retention and attrition	Yes – based on transactional history and on data from reviews
Customer satisfaction	Yes – based on data from reviews.

[68] Examples of stakeholders' questions: What is the company's CLV? Which emotions prevail in our customers? Who are the most profitable customers based on the margin? What products do the customers with the highest satisfaction score purchase? What topics did the customers with the negative sentiment mentioned? Which personality types bring the most purchases to the company?

Analysis Requirement	Possible to perform with the designed metrics and the data model?
Customer scoring and segmentation	Yes – based on results of metrics.
Customer state in the journey	Yes – based on transactional and data from reviews.
Opinion target analysis	Yes – the targets are mined during the modelling phase with text analytics.
Product/service experience analysis	Yes – the product perspective is not omitted, ensured with the product's dimension.
Trend analysis	Yes – the date dimension enables to predict the trends of the metrics.
Data Maintenance	Yes – data maintenance is ensured by the nature of the BI solution and the presence of date dimension.

The criterium 4) *"To propose the following marketing actions based on the suggested metrics from Table 5.1"* was satisfied with the list of marketing activities in section 6.2.6.3.

The **trade-offs** questions can be answered by the performance of the employed methods mentioned in section 6.2.5. As the modelling was performed based on new dataset not annotated before and manual annotation did not offer satisfactory results due to complexity of the task, the author measured the performance of chosen methods based on the earlier annotated dataset of restaurant reviews (Steinberger et al. 2014). The sentiment task's F1-score was measured with the result of 0.61 and 0.78 for positive class. The author supposes to gain better results with refining used lexicons. The aspect detection was due to the rule-based approach very successful with the accuracy of 98.06%. The results of emotion mining were predicted with 90% accuracy and loss of 0.23. The reason is a large amount of training data of the utilised deep learning tool. The detection of personality traits was only experimental using simple heuristic approach and cannot be further validated. The LDA model required substantial human work at the beginning, but with further utilisation it is assumed to gain better results. For manual annotation, a more detailed specification is needed to correctly label the contributions in the next engineering cycle of treatment design.

In the case of **sensitivity**, the potential issue can occur if any of the freely available tools would be unavailable or not able to process the desired amount of the data. The commercial tools are still an expensive solution for smaller companies; the code of text analytics models would have to be rewritten, which would take a certain amount of time. The application of the methods is specific to the stakeholders' environment and available data but transferable to any other textual dataset with some refining. The models would have to be learned on new data; manual annotation would be necessary for supervised learning. The author recommends examining different classifiers to compare the accuracy of the results.

The advantage of the solution is a centralised place where stakeholders can consume data which are currently fragmented and visually presented across different systems on an ad-hoc basis. New data sources can always be integrated.

The stakeholders were satisfied with the result of the treatment design and after minor adjustments were ready to move to the phase of implementation.

6.4 Implementation

After the design validation phase, the author implemented the Customer Experience data model to test the validity of the treatment in the stakeholders' environment with available technologies. Based on the results from design validation, the stakeholders agreed with the author to implement the sentiment and aspect detection. The emotion and personality mining will be forwarded to the next iteration in the engineering cycle.

The technological architecture of the solution is depicted in Figure 6.23. The PostgreSQL database serves as a data warehouse of the whole BI solution where a sub-part is also Customer Experience data model. As the performance of PostgreSQL was not sufficient to process text analytics models, the author decided together with stakeholders to use high-performance cloud SQL database Snowflake[69] with the use of Keboola[70] ETL platform which enables to run transformation in different environments. All the necessary lexicons were loaded to Snowflake together with necessary tables for modelling in R. The R environment is running using the Docker[71] , and all the results are loaded back to Snowflake. All the modelling is processed in R including modelling of CLV and RFM. The Snowflake serves as storage for intermediates results, mainly of the raw data and the textual stage. Also, the rule-based approach for aspects detection is written in SQL and processed by Snowflake. The aggregated results are further sent back to PostgreSQL data warehouse where the data joined the structured data. In the end, the data are sent to business analytics software Power BI[72] by Microsoft, which serves as a reporting tool, but also as a final analytical model. Power BI connects to PostgreSQL database to import the necessary data for reports creation. The advantage of this particular solution is the possibility of connecting to many data sources, thus, building the analytical data model for Customer Experience Measurement based on data from various sources. The other sources used by the stakeholders for monitoring the marketing (campaign performance and customer

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[69] More about the product at https://www.snowflake.com.
[70] More about the product at https://www.keboola.com/.
[71] Platform for running programs within a virtual operating system.
[72] More about the product at https://powerbi.microsoft.com/cs-cz/.

behaviour on the web) are currently directly loaded to Power BI where the analytical model is completed by data from these sources.

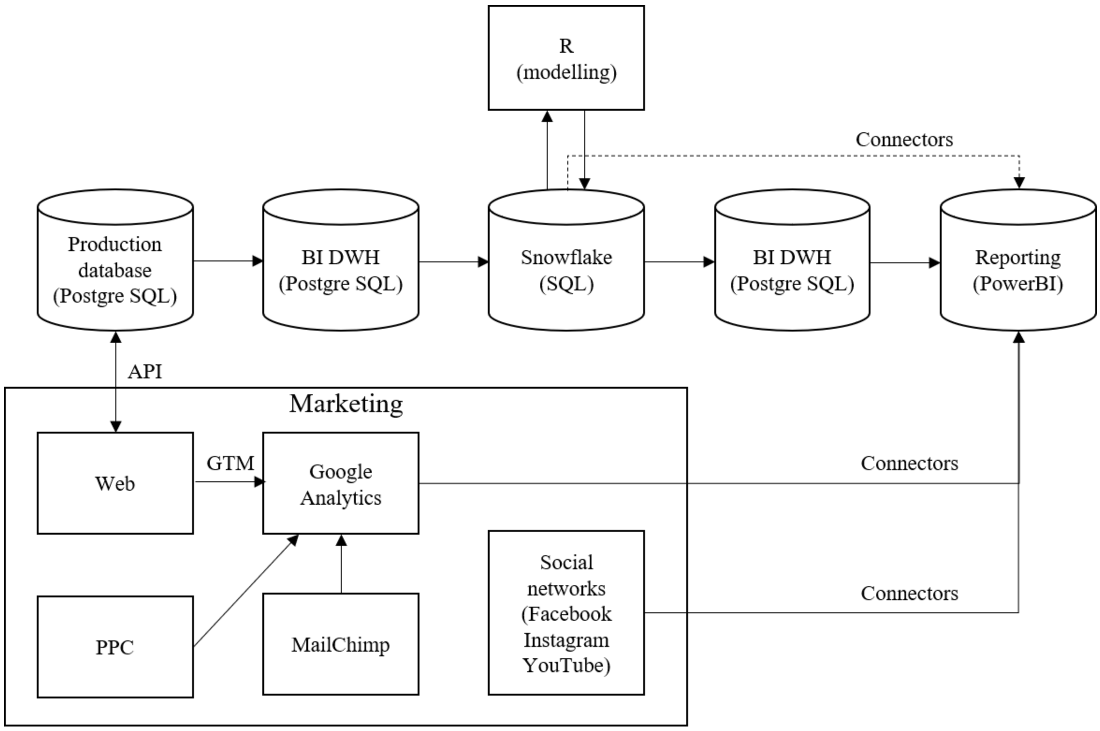

Figure 6.23: Technological architecture of the solution

The dotted link between Snowflake and Power BI in Figure 6.23 represents the possibility to load data to Power BI directly from Snowflake as the connector in Power BI is also available. The plan for next iteration of the engineering cycle is to use Snowflake as a data warehouse where the data from all systems will be stored at one place, then the Power BI will connect only to Snowflake to gain all the necessary data.

The close co-operation of the author in the analyst role, the suppliers of the IT solution and stakeholders were necessary. All the changes in the data warehouse were consulted with the internal BI analyst of the company and three-party database programmers who deployed specific ETL within the PostgreSQL solution. The ETL in Snowflake and scripts in R wrote the author.

The employees of the company who are consumers of the reports had to understand the essence of the metrics to be able to work with them correctly. Also, employees defined their specific requirements on reports after assessing the reports created in the treatment design phase. The key indicators and benchmarks were added to the reviews to monitor performance. Finally, the solution has been published online for daily usage.

6.5 Implementation Evaluation

The stakeholders evaluated implemented treatment after three months since the deployment of the solution in the company. According to (Wieringa & Morali 2012), during implementation evaluation, the author asks explicitly for the effects of the treatment under evaluation. The following text is a summary of the knowledge gained during the evaluation from the stakeholders next to author's perceptions. The implementation is evaluated from the perspective of implications to Customer Experience Management. The implications are directly connected to the mitigation of the barriers 1-6 (*B1 – B6* in the following text) detected in the research in section 3.3.3.

6.5.1 Implications to the Customer Experience Management

The implementation of the Customer Experience multidimensional data model started to have a direct impact not only on the management of the Customer Experience in the stakeholders' company but also to financial management. As the textual data are connected to the transactional data, stakeholders could begin to map the financial value of transactions to the satisfaction and understand how a change in Customer Experience directly impacts revenues. *(B2)*

The artefact of Customer Experience model helped with a scope definition of measures and metrics which are suitable in the specific business case of stakeholder's company. *(B6)* The BI analyst further said*: "Without the organised Customer Experience model based on defined metrics which will be monitored in the long term, I think, we would struggle to understand what is working and what is not as all reports were made on an ad-hoc basis when a question was raised".* Stakeholders consider the unification of the customers and their division to buyers and consumers as an essential benefit. Now stakeholders can target their marketing activities to both categories separately. The goal is to transform a consumer into a buyer. They can monitor when the consumer became a buyer as the customers who buy the products usually do so for the third person. When analysing consumer's textual data, the direct marketing message can be targeted according to the content of the reviews. *(B5)*

The implemented model is extensible. The stakeholders can add new fact and dimension tables or define new metrics according to their needs. The BI analyst did so and extended the model for certain financial indicators to measure the correct margin brought by single customers. (*B2*, *B4*) The new data sources can be integrated. In the next iterations, the stakeholders plan to extend the textual stage for the data from web chat. *(B4)*

The change would not be possible without the full executive support of the CEO and managers of the company. The customer-oriented companies must gain executive support, build a Customer Experience team to lead the transformation (which was the author of this thesis and the dedicated BI analyst) and create a shared understanding of the intended experience which will be fully embedded in the organisation with principles and processes supported by all employees. Last, but not least, all employees of the company were acquainted with the new reporting as some of the reports were developed on their requests to meet specific needs. *(B6)*

Primary consumers of the reports are the customer-facing employees – staff of the marketing department, customer support and direct vendors. The consolidated reporting enables them to communicate with the customers consistently through all available channels based on shared knowledge. All the employees have the same information as the customer insights are shared through the organisation. They can immediately assess the plan or reality and save the time they usually spent when asking somebody else for information. With the consolidated reporting, the company does not need to hire external consultants to build specific reports in the future, which will lead to cost reduction while still maintaining customer satisfaction. *(B1)*

The multidimensional view of the reports enables employees to look at the data from a different perspective without having to read the original feedbacks from the customer. *"We immediately see the issues from the reports. When something needs deeper analysis, we find the original comment."* Stakeholders can view and filter data according to their interests and take appropriate actions to manage Customer Experience. The consolidated reporting serves as a baseline for further exploration of the problems and opportunities by relevant employees. Long-term monitoring of metrics allows finding patterns in Customer Experience and taking the corresponding approach or pro-actively preventing certain situations. *(B3)*

"For us, it is essential that next to the retrospective evaluation, we have also the option of predictions. The prediction of CLV helps us with planning the budget for campaigns and thanks to information from textual data we can also figure out how the messages will look like since customers mentioned specific things in the past. The content analysis is beneficial at this moment. We see that even we have an excellent rating in the form of scales overall, there are dimensions to improve. Also, we can focus on problematic providers of the experiences – the dimension I added to the data model", said the BI analyst of the company. *(B3)*

All mentioned implications shift the stakeholders' company to a higher level of Customer Experience maturity. The stakeholders realise that for further development, support and maintenance of the solution, a dedicated person is required. *"We will need a dedicated employee to maintain the models and their re-training. Somebody will also have to maintain the lexicons and extend them for domain knowledge as our products contain many specific terms".* The company also wants to simplify the architecture of the solution with the transition to new cloud ETL with a dedicated database.

6.6 Summary

In this chapter, author validated the designed artefact in the real-world environment of a medium-sized e-commerce company operating in the Internet environment as an intermediary of selling experiences through case study following the TAR method. The validation aimed at the textual stage of the designed Customer Experience multidimensional data model and applied the text analytics to mine the Customer Experience elements of satisfaction, emotions and personality from customer reviews as objective *O3*. The deliverable *D3* brings a lexicon-based approach for customer sentiment, rule-based approach for aspects detection, Latent Dirichlet Allocation for aspect categories detection and deep-learning for emotions mining, and clustering for personality detection following the CRISP-DM methodology on its highest level. The chapter also contributed to the *RQ2: How to incorporate Voice of Customer and its textual analytics into Customer Experience Measurement to further understand Customer Experience during the customer journey?*

An important step was data processing. As the Czech language is very complex, inflectionally rich language, the detection of dependency relations was essential for further analysis of aspects. The manual annotation turned out to be a failure due to the complexity of the task; the rule-based approach implemented by the author showed much better results with 98% accuracy on a previously annotated dataset. The emotions were predicted with a deep learning algorithm based on annotated data from the different corpus with excellent results. The experiment of personality traits detection used the method of translation of contributions to the English as commonly used dictionary LIWC in the research of personality is not translated to Czech yet. For sentiment assigning lexicon-approach was performed with satisfactory results, but in the future, the author recommends supervised learning as current lexicons are not fully developed. The selection of methods was guided by the requirements on mining the customer elements in Chapter 4 and their feasibility in the concrete case.

The exploration of whether the textual evaluation reflects the numerical evaluation confirmed the previous research findings that reviewers tend to add what they did not like to positive rating and conversely.

Next, the author expanded the textual stage for the analytical stage to gain the complete Customer Experience data model based on metrics designed in Chapter 5 and proposed a set of reports to monitor Customer Experience which were divided to three perspectives to reflect the level of aggregation – company, product and customer. The last one enables a single customer view of his state-of-mind and behaviour.

After the design validation, which fulfilled the stakeholders' goals, the minimal viable product was implemented in stakeholders' company and evaluated by stakeholders with the impact on Customer Experience management as an answer to *RQ3*. The implications are linked to barriers (section 3.3.3) which are mitigated with the implemented artefact. Overall, the company improved the value for the customer, that means customer value from the customer perspective.

Among the key findings of the validation belong:

1) The domain knowledge is essential for the building of the models.
2) The selection of the models depends on the business case, language, available data, technologies and the degree of accuracy that the stakeholders are willing to accept.
3) The change in the company costs time and human capacities, and everyone in the company must be aware of the change and understand the transformation in order to succeed.

Chapter 7

Validation of the Artefact with Expert Opinions

This chapter represents the results of qualitative validation of the artefact with expert opinions. In contrast with the validation by the TAR method in Chapter 6, which is focused on a realistic version of the artefact interacting with a real-world context implemented in a single company, this chapter attempts to validate the needs, requirements and business context that vary among companies. The artefact was submitted to a panel of experts in accordance with Wieringa (2014, p. 63), who visualised how such an artefact will interact with problem contexts imagined by them and then predict the possible effects.

7.1 Methodology

The experts' opinions were gained by conducting the individual in-depth interviews. The main objective of the interviews with experts was to get feedback on the proposed Customer Experience data model and designed measurement. The experts were faced with the artefact and its treatment. They validated the proposed metrics and the Customer Experience data model and offered possible ideas for the modification of the model. An expert for the purposes of this interview is defined as someone who:

1) who conducts and publishes research on Customer Experience or text analytics,
2) or is the business practitioner operating in the area of customer relationship management or customer analytics.

The expert panel is listed in Table 7.1. All of them agreed with the disclosure of their name, position, affiliation, and the university where they conduct their research. The experts received questions by email, along with the submitted artefact and its treatment. In addition to the questions, the material sent to the experts contained a brief introduction to the doctoral thesis with the context of the artefact, following the presentation of the Customer Experience construct, the Customer Experience data model and defined measurement, and the designed treatment from Chapter 6. Interviewees were kindly requested to provide feedback including their opinion on the effects of the artefact. Afterwards, individual in-depth interviews were conducted. All interviews were conducted from September to November 2019.

Table 7.1: A group of experts on Customer Experience

Expert	Name and Position	Affiliation	University	Interview Type and Length
Expert 1 (E1)	Tomáš Šalamon, CEO	Incomaker[73]	Department of Information Technologies, University of Economics, Prague	In-person, 60 minutes
Expert 2 (E2)	Jan Mayer, CEO	Dataweps[74]	Division of Information and Library Studies, Faculty of Informatics, Masaryk University	In-person, 40 minutes
Expert 3 (E3)	Karel Jaborník, International Customer Management CoE	Teradata	-	In-person, 60 minutes
Expert 4 (E4)	Jiří Hana, Senior Researcher	Geneea[75]	Institute of Formal and Applied Linguistics, Charles University in Prague	In-person, 60 minutes
Expert 5 (E5)	Pavel Jašek, Analytical Lead	Google	-	In-person, 80 minutes
Expert 6 (E6)	Adam Šilhan, Head of Marketing	Igloonet[76]	Division of Information and Library Studies, Masaryk University	In-person, 60 minutes
Expert 7 (E7)	Kateřina Veselovská, Semantic Data Science Lead	Deloitte	Institute of Formal and Applied Linguistics, Charles University in Prague	In-person, 50 minutes

The goals of the validation by experts were:

- To gain the feedback on designed artefact forming the Customer Experience Measurement: The Customer Experience data model and proposed measurement. To verify the correctness of the selected metrics and the way they are stored.
- To assess the validity and usability of the artefact in Customer Experience Management.
- To assess the application of the text analytics methods in the treatment design (Chapter 6).

In Design Science, the four kinds of knowledge questions (Wieringa 2014, p. 60) must be answered similarly to the validation of treatment in section 6.2.6.3.

[73] https://www.incomaker.com/cs
[74] https://www.dataweps.com/cs/
[75] https://www.geneea.com/
[76] https://igloonet.cz/

1) Expected effects questions (understanding how the artefact produces effects in the studied context): What would be the impact of the artefact in the companies you work with? How would the companies respond to the designed model and measurement in accordance with Customer Experience Management?

2) Expected value questions (understanding if the effects satisfy requirements): Would the artefact satisfy your analysis requirements regarding the Customer Experience Measurement? Do the designed Customer Experience metrics and dimensions satisfy the needs of the companies relating to Customer Experience Measurement and management? Is there any critical part of the data model or measure missing?

3) Trade-offs questions (understanding the alternative artefacts): Would you approach the measurement of Customer Experience with the integration of textual VoC differently?

4) Sensitivity questions (assessing the artefact's effects in alternative context): Is the data model transferable to different business domains you work with? Would you change the approach to the Customer Experience Measurement and Management in the given company's context? Would you extend the artefact for new sources of data, dimensions, fact tables and metrics?

7.2 Results

According to Wieringa (2014, p. 63), the goal of expert opinion is to gain insights into findings they observe when they imagine the artefact in the problem context. The stated questions served as a guide for their insights; not all suggested questions must be answered in extensive detail when experts confirmed they agree with the benefit. The results present a list of insights structured according to the goals of the validation. The insights are directly connected to the mitigation of the barriers 1-6 (*B1 – B6* in the following text) detected in the research in section 3.3.3.

7.2.1 Evaluation of the Customer Experience Data Model

The artefact was found to be relevant and helpful for the stakeholders' goals. The design of the model was assessed as sophisticated and timeless. It does not mean that it is a complete solution, but it is a standardised denormalised data model, which can be extended or reduced based on the available data. Any given company can choose what metrics to measure and which tables to load or add as new tables. Experts emphasised the modularity of the solution. The parts of the model seem timeless thanks to the dimensionality. Instead of ad-hoc analysis, the thesis attempts to create an integrated system from which the individual parts can be used.

Expert E3 point out, that in contrast to robust commercial solutions which are always black-box solutions, the artefact is transparent and affordable also for smaller companies. Expert E1 opposes that for smaller companies, the solution might be expensive if it is not tailored to the specific industry. This fact is not a shortcoming of the model but a development phase that emerged from the primary research that needs to be brought into the application, and that demonstrated additional benefits. Although the artefact does not act as an application, the experts praise, that the artefact describes how to collect the data, store the data, and the following actions which offer strategies according to defined segments. *(B1, B4, B6)*

It is necessary not to understand the model dogmatically; there is a degree of adaptation and enlargement (for example, customer - consumer - approver) in a specific business case, but still in the same usage of the methodology. Importantly, the thesis newly develops some of the problems that have not been sufficiently discussed and identified before: customer-user relationships - definition of who is the customer and who is the consumer. The relationship is not unambiguous; the company can also benefit from the customer who purchases for someone else who is satisfied and writes positive reviews. This behaviour increases the likelihood of a customer, after buying for someone else, buying again. Conversely, one consumer dissatisfaction can lead to the loss of many other consumers.

According to expert E3, the Customer Experience Model breaks the existing silos of marketing teams, operation teams and customer care that need to share the data *(B1)*. Usually, VoC is solved only in relation to social media. Companies that already work with CRM together with campaign data usually track their customers' complaints and reviews. What these companies lack is NLP expertise. Experts E4 and E7 agreed that, unlike abroad, in the Czech Republic text analysis is still not a priority, but is just nice-to-have.

The logical model of the data mart implies the form of data at the input. It is unclear who processes it, but that is the matter of the application and implementation (web crawler, API to systems and similar). Experts think that the approaches used in the artefact can reduce the costs of analysing the textual data from the Internet environment and enable its scalability. *(B3, B6)*

Expert E5 expressed concern about the sustainability of the model, whether it is still going to be valid in five years. E7 stresses the need for re-training of data, where there is often a problem of inconsistency. It is necessary to have the right employees to sustain the model – a role for text analytics, a role for Business Intelligence. The domain knowledge is critical. According to expert E4, a person to build the company's ontology is essential.

Experts agreed that the artefact would be easily transferable to those companies that are on higher levels of BI maturity. In the expert E1's opinion, many organisations would be interested in implementation – mainly e-shops or travel companies. It is advisable to transfer the model to other domains where there is much textual feedback from customers. The Customer Experience has the potential in the hotel domain, where there exist many types of interactions and feedback through different channels – emails, calls, contact at reception, reviews, or companies selling energy. Expert E6 works with an international company operating in the travel sector that can benefit from the implementation of the artefact. In his opinion, the many languages of the textual inputs could represent the barrier of implementation as textual models would have to adjust.

7.2.2 Evaluation of Customer Experience Metrics

Experts agreed that current methods of customer surveys should become more engaging and conversational, and be performed through the channels the customers interact with to gain their feedback. From their perspective, the response rate to traditional customer surveys is declining, especially among younger customers; thus it is more and more essential to analyse the textual data from the sources where customers already express their opinions and feelings about their experiences. To maximise efficiency, VoC should operate with information from multiple sources. From this point of view, the artefact can be a solution to evaluate experiences across numerous channels the customers communicate through. *(B4)* One expert can imagine using the aspect detection to analyse the conversations through the Facebook Messenger app – what the customers mention and how often. Expert E5 would add voice analysis to the solution, which can be a subject of further research.

Also, according to expert E6, the stronger the sector is in terms of retention, the higher is the impact of VoC (and the artefact) in the business. Sectors with predominant one-time buyers can correct current problems or improve their offering for future business with the implementation of the artefact. Those with stronger retention affinity will benefit more greatly from increased retention.

According to experts' opinion, the metrics and dimensions cover all areas needed for the evaluation. Expert E6 might add a metric of overall costs attributed to the customer (advertising costs, cost of customer support). In the travel industry where the expert works, it is essential to know the cost of customer support. Expert E1 would add the metric of the frequency of use and its development over time for some types of services such as SaaS or online services. If the customer restricts the use of the service, it is usually an indicator that something is not right (e.g. the service quality is not right, the needs of the customer have changed).

Almost all experts agreed that it is important to make the theme of emotions and personality part of the solution - firstly, for a clear link to the customer and Customer Experience, and a link to what the company can do with it. However, expert E4 does not see such a business value in detecting discrete emotions because he cannot imagine their use. *"What does it mean, when a customer says 'It is expensive', and the detected emotion is disgust?"* According to him, personality traits describe users more, and in combination with aspect detection can bring valuable insight. *"If I have neurotic customers, I do not put so much emphasis on their complaints, because they act accordingly to their personality; however, they buy a lot. When these customers write a positive comment, I know it is a big compliment."* Expert E7 see high value in emotion and personality detection to customise the communication style, for example, in chatbots. *(B5)*

Experts appreciated the demonstration of the solution in the dashboards – they understand them not as a final form, but rather as a blueprint, useful for implementing the concept and deciding on the extent of solution implementation in the company (if the company does not have enough textual data, it will only use transactional data). *(B4)* Expert E5 recommends creating a procedure for this decision. The experts emphasise well-used combinations of all types of segments and metrics which define who is who, which experts consider as descriptively excellent. Correspondingly they highlighted the monitoring of metrics over time and maintaining the customer perspective. The time dimension adds a critical insight into the customer journey. *(B5)* Simultaneously, this definition can lead to a prescriptive causal application where experts see room for development and search for insight. Expert E3 suggested the reports to show what the cost of one Customer Experience point is (a scale based on chosen metrics defined by the stakeholders). Such a metric would demonstrate the financial impact of the Customer Experience to the business and could serve as a predictor. The question is what to compare; the expert suggests the average of the customer base. *(B2)*

Experts E5 and E2 recommend dividing the marketing activities into strategic and tactical use scenarios where a problem would be identified as a trigger that would activate a marketing activity or categorisation of the customer to the specific segment. Expert E7 warns that customers can react negatively to well-targeted marketing (the "big brother effect"). It is essential to know how to convey a personalised marketing message. *(B5)*

7.2.3 Evaluation of Applied Text Analytics Methods

Experts agreed that the processing of unstructured data in a structured way is effective because they can be measured and easily connected to the organisations' internal data and metrics. Current technologies enable relational processing without the loss of efficiency. *(B3, B6)* Expert E1 emphasises the methodology defined by primary research. He admitted that he would proceed in the same way to obtain a general model. *(B6)* Expert E4 confirmed from his own experience that the scale-rating does not correspond to the sentiment detected in the text. He considers the numerical expression of metrics to be essential for stakeholders' understanding. At the same time, stakeholders do not want to lose the content of the text. The aspect detection was confirmed as the best approach to presenting the content. *(B3)*

Experts agreed that the benefit is not in designing the text analytics models and their specific implementation, but in designing the logical model and the relevant metrics and creating instructions on how to work with them using processes and methods. From the experts' point of view, for business use, it does not matter which specific technique is used to calculate the metrics and what methods fill the tables – their weight in Customer Experience Measurement can be adjusted. *(B6)*

Experts also highlighted the direct implementation of the solution in the case study. The author found the scalable application that fitted as one of the signals in the model and is good enough with some degree of accuracy, that the stakeholders were willing to accept because of the riskiness of the further actions. According to the expert E5, some parts of the solution are unnecessarily described in great detail, which is a clear added value to the thesis that was not found on the market and in the research solutions or other research that would support the used procedures (e.g., personality detection). *(B3)* In his opinion, this is not a problem of the author, but the problem of the methods, however, not a barrier to using them. There are some other problems associated with each data source, technique and application. Expert E1 also highlights the detail that allows the replicating of the primary research. *(B6)* On the other hand, the same expert and expert E7 expressed concerns whether general conclusions could be drawn from one case study. For example, the question is, how much the models linguistically overlap between domains – how much transfer learning is necessary.

The subject of further research is to validate that the methods are of the highest quality. They can then be easily replaced in the model. For example, if the Big Five model is not considered to be state of the art in the future, it could be replaced by a new one approved by psychological research. *(B6)* According to experts E5 and E7, for some techniques in text analytics, it is not necessary to have well-defined clusters that correspond to psychological classes, but rather to show the heterogeneity of the customer through the clusters and anomaly detection. According to expert E7, customers who behave differently from their written expressions should be detected. Moreover, according to expert E5, in supervised methods, the coherence of annotators is a major problem, mostly in assigning emotions. Expert E1 recommends fuzzy logic for determining the range of emotions. Expert E6 would try the Word2Vec approach but admits it might not be ideal for this use case.

Expert E5 recommends diagnosing metrics by, for example, sentiment volatility and identification of the soft boundaries between segments and resulting metrics (confidence interval). The artefact works with a measure of inaccuracy and the probability of output. There should be a clear link to further research which should validate the methods in terms of linguistics, psychology and similar. Expert E7 would add conversion as a success metric.

Also, it should be solved how to work with missing data - when reviews from all customers are not available, and the feedback is only from some percentage of customers. That could represent an issue from the company perspective. Psychologists work with the fact that only some sort of users responds. How would it impact the Customer Experience? How should the customers without feedback be treated? It is necessary to find the right method for extrapolation. This issue is partially addressed by the reviewability metric, which shows reviewers' share of total purchases (for example, 100% of complaining customers are only 2% of the customers who purchased the product). There was another question about how to measure experience with missing transaction data – for example, for companies whose intermediary is a supermarket. The problem of data quality was also pointed out by expert E7, who claimed that in business the integration of the VoC data from different sources has not been solved yet and the companies are not able to map the same customer from different sources. E7 expert sees multilingual customer feedback as another problem. At the same time, expert E7 appreciates that the author of this thesis is aware of the limits of text analytics and continuously mentions them in the thesis. *(B3)*

Expert E4 commented on the mentioned drawback of aspect detection using syntactic rules in section 6.2.5.3 where a single aspect could be detected multiple times as a part of different n-grams. In the expert's opinion, this is a part of the behaviour of the system which represents individual levels of detection (in terms of their granularity) that could be categorised upon request of the stakeholder. *(B3)*

Expert E7 concluded that the work is very broad, which is difficult to cover and combine. Each research topic (personality, emotions, sentiment) could be solved in a separate thesis.

7.3 Summary

This chapter evaluated the artefact from the perspective of seven experts who have expertise in business and academical research. As a result of in-depth interviews with the experts, it can be stated that Customer Experience construct reflects the current knowledge in Customer Experience and contains the substantial Customer Experience elements, their relationships and the dynamics of the customer journey. The experts agreed with the research that the topic of emotions and personality is important to be part of the solution, firstly, for a clear link to the customer and Customer Experience, and a link to what the company can do with it. The metrics and dimensions cover all areas needed for the evaluation. Since the artefact works with a measure of inaccuracy and the probability of output, other diagnostic metrics were recommended to add to the artefact.

The approach to the processing of text data in a structured way was found suitable. Numeric metrics alongside text content are critical to stakeholders. The highest value was observed in the design of the logical model and the relevant metrics and creating instructions on how to work with them using processes and methods. The artefact is transferable to different business verticals with the assumption that the model and metrics must be adjusted to a particular business case. Reference models for different verticals can be designed in future research.

According to experts, the specific implementation of text analytics methods is not that important for the artefact as the methods and models can always be replaced. The application of the methods always corresponds to some degree of accuracy that the stakeholders are willing to accept because of the riskiness of further actions. The experts highlighted the detail of the methods implemented in the case study. At the same time, they stress the need for further case studies for different business domains in order to draw general conclusions about the text analytics approaches and their sustainability.

Based on the experts' answers, it could be stated, that the artefact mitigates the barriers detected in section 3.3.3 and that the artefact fulfilled stated objectives in section 1.2.

Chapter 8

Discussion

This chapter discusses findings resulting from this thesis based on literature review, designed artefact, treatment and its validation, and formulates main conclusions. The chapter also summarises the findings of the research questions stated in section 1.3. Objectives. Research questions are mapped to their respective sections; deliverables are summarized along with the objectives and their benefits. As a final point, recommendations for further research are outlined.

8.1 Meeting the Objectives of the Dissertation

The primary purpose of this thesis was to design and validate the Customer Experience data model extended by the information gained by the analysis of textual VoC in order to help companies improve their Customer Experience Management. The author stated three objectives *O1 – O3,* which were fulfilled with three deliverables *D1 – D3*. Table 8.1 maps the objectives and deliverables to relevant chapters. Research Questions *RQ1 – RQ3* proposed based on objectives are answered in the next section.

The objective *O1* was fulfilled by the deliverable *D1* designed in Chapter 5. *D1* presents a research artefact based on the theoretical knowledge from the literature review. The designed data model represents the application of the Customer Experience construct (*D1a*) that the author proposed in Figure 2.3 in section 2.4. The data model is divided into the textual (Figure 5.7) and analytical (Figure 5.8) stage where the analytical stage is dependent on results from the textual stage. The data model was validated during the treatment design in Chapter 6 and with expert opinions in Chapter 7.

The objective *O2* was satisfied by the deliverable *D2* designed in Chapter 5. *D2* and *D1* together represent a research artefact. The set of metrics is listed in Table 5.1: Metrics and Indicators in Customer Experience Measurement. The *D2* represents the highest layer of the Business Intelligence framework (see Figure 5.1). The periodical reporting of proposed metrics in sophisticated dashboards (section 6.2.6.2) serve for the management of Customer Experience, which in this thesis is understood as a construct of share-of-mind metrics. The emotions, sentiment and personality traits are detected from textual VoC data with automatic text analytics methods (*O3*). The mined information is joined with other operational, transactional and behavioural structured data from different EIS in the unified multidimensional data model (*O1*). The model provides a source of data for comprehensive metrics measurement and reporting. The measurement on joint data contributes to the detection of current constructs such as loyalty or engagement. Dimensions by which metrics can be drilled, sliced and filtered are listed in Table 5.2: Dimensions in Customer Experience Measurement. The validation of the *O2* was partly performed with the satisfaction of stakeholders' goal *SG2*.

The objective *O3* was achieved in Chapter 6 by deliverable *D3* along with the stakeholders' goals *SG1* and *SG2* defined in section 6.1 during the validation with the TAR.

SG1) Incorporation of customer reviews to the current Business Intelligence data model and creation of the textual part of the Customer Experience data model

SG2) To automatically report information from customer reviews next to other available customer data in consolidated Customer Experience Measurement.

The stakeholders' goals were satisfied by fulfilling the criteria defined in 6.2 Treatment Design. The author performed a mixture of text analytics methods and detected sentiment, emotions and personality from the text following the CRISP-DM methodology to satisfy requirements for text analytics methods to mine Customer Experience elements defined in section 4.2.

The lexicon-based approach was used to detect the sentiment, rule-based approach to detect aspects, LDA method to detect aspect categories, and for emotion mining, a combination of lexicon-based approach and deep learning was performed. The experiment with assigning personality was processed with a rule-based approach and clustering using the LIWC dictionary. Extracted information by these methods has been loaded to the textual part of the Customer Experience multidimensional model and combined with other structured customer data in the analytical part. The author proposed reports based on defined Customer Experience metrics (results of *O2*) and divided them into three perspectives to reflect the level of aggregation: company perspective, product perspective and customer perspective (section 6.2.6.2). Furthermore, marketing activities suitable for the company of stakeholders were proposed (section 6.2.6.3).

Table 8.1: Meeting the research objectives of the thesis

Research Objective	Deliverable	Relevant sections	Meeting the objective
O1) To design the Customer Experience multidimensional data model enhanced with storing the information extracted from textual VoC.	D1) Multidimensional Customer Experience data model	Chapter 5 Customer Experience Data Model 5.6 Textual Stage 5.7 Analytical stage	Yes
	D1a) Customer Experience construct as an enhanced conceptual model	2.4 Customer Experience Construct	
O2) To enhance Customer Experience Measurement with new elements of customer sentiment, customer emotions and personality traits.	D2) Set of metrics evaluating Customer Experience from the customer's perspective based on elements of sentiment, emotions and personality traits.	5.3 Design of Customer Experience Measurement	Yes
O3) To validate the textual part of the Customer Experience model with the application of text analytics methods for extracting information from textual VoC.	D3) Application of text analytics methods suitable for determining and measuring Customer Experience elements based on VoC textual data.	Chapter 6 Validation of the Artefact with the TAR Method 6.2 Treatment Design	Yes

8.2 Answering the Research Questions

The author stated three research questions to support the objectives of the dissertation. Firstly, the current situation of the usage of VoC within the Customer Experience was described as an answer to the question *RQ1*, secondly, the problem of incorporating textual data to the Customer Experience was investigated by the question *RQ2* and lastly, the implications of the enhanced Customer Experience Measurement model into the Customer Experience Management was examined by the question *RQ3*. The findings to research questions were continuously contributed in the content of previous chapters; Table 8.2 maps the research questions to the relevant chapters/sections that answer and discuss the questions in more detail.

RQ1) What is the current situation in the use of Voice of Customer within the Customer Experience Measurement?

This question was answered in Chapter 2 from the perspective of the current research, in Chapter 3 as qualitative research conducted by the author in Czech B2C companies and partly in Chapter 4 from the standpoint of text analytics approaches in the research where VoC can contribute as a source of textual data. Chapter 2 discussed different approaches to the measurement of VoC within Customer Experience research. Section 2.2 emphasised the role of WoM in Customer Experience as a prevalent source of data in its structured and unstructured form for monitoring customer satisfaction – the essential element of Customer Experience – in the free environment of the Internet. Section 2.3 debated the role of VoC in the expectation-disconfirmation construct. Most researchers evaluate the experience with surveys, interviews and focus groups or measure elements of Customer Experience with structured behavioural or transactional data as a standalone quantitative metrics. Another dominant source of VoC is customer reviews where the evaluation of structured information in the form of Likert-type scale ratings and assessment of their effect on purchase decisions with some research focusing on sentiment predominated. The inclusion of text analytics into Customer Experience is still a new area of the research. The typical approach in Customer Experience is to investigate sample data from one source of VoC for one specific goal instead of an automatic periodical exploration of data. The current research showed the need to create a coherent Customer Experience construct (designed by the author in section 2.4) that considers the known monitored Customer Experience elements, measurable by both structured and textual data. These elements cannot stand alone, but they affect each other as the customer journey is a dynamic process. The influence of the perceptions and attitudes of customers must be included; thus, emotions, personality and sentiment were proposed as qualitative indicators of the experience measurement

The situation in the usage of VoC within Customer Experience in the environment of Czech B2C companies operating within the Internet environment was described by qualitative research in the form of focused interviews in Chapter 3. This research was also published in the author's article (Šperková 2019). Manual evaluation of textual data with an emphasis on satisfaction still prevails in the Czech companies, and no comprehensive approach is utilised. The researched companies can be described as immature in Customer Experience Measurement. The author also defined barriers to achieving the full potential of analysing VoC within Customer Experience in section 3.3.3.

The approaches to the automatic analysis of VoC with text analytics were described throughout Chapter 4. The methods of automatic prediction of personality traits and emotions from textual data were mentioned in section 4.6. The literature review in text analytics pointed to the gap in the integration of the knowledge from analysing VoC to Customer Experience. The studies in sentiment analysis neglect the customer perspective and analyse the aggregated sentiment from the product/service/organisation perspective without being linked to the customer. The implication of the text analytics results into the marketing and Customer Experience supported by any replicable method describing the process is generally missing. For marketers, practical use is still not fully uncovered. Generally, marketers use separate systems for monitoring of WoM. There are also missing studies integrating the results with other structured customer data.

RQ2) How to incorporate Voice of Customer and its textual analytics into Customer Experience Measurement to further understand Customer Experience during the customer journey?

This question was answered primarily in Chapter 5 during the artefact design and in Chapter 6 during the treatment design in a real-world environment based on the theoretical knowledge from the literature review in Chapter 2 and 4. The answer to this question is supported by all the objectives as seen in Figure 1.3: Research methodology framework. First, the author defined elements of Customer Experience, which can be measured by textual VoC in Chapter 2 (satisfaction, emotions and personality). Following the Customer Experience construct as an enhanced conceptual model (Figure 2.3), the author proposed to design a multidimensional data model (deliverable *D1*) and set of metrics (*D2*) for measuring these elements based on information from textual and structured data in Chapter 5.

The current methods of evaluation of Customer Experience are concentrated at the end of the customer journey while ignoring the underlying issues and concerns resulting from the experience during the customer journey. The collection of all customer data from multiple channels, with which the customer interacts during their journey, into the single storage with unified access enables to look at all customer data from the customer perspective according to the time dimension and evaluate their experience on the near real-time manner and their state in the journey.

The author chose the Business Intelligence approach (see Figure 5.1: BI framework for the process of VoC integration to Customer Experience) with the use of textual ETL to extract the elements of Customer Experience from textual VoC. The information is stored with other structured data regarding the customer and their behaviour from various sources into the unified data model. The model contains dimension and fact tables with sentiment, emotions and detected personality traits attributes related to customer and relevant comments. The unified storage with all customer's data leverages the comprehensive measuring of Customer Experience with metrics defined in Table 5.1. Stakeholders can explore the metrics from different dimensions listed in Table 5.2. The process flow for the model application represents Table 5.6.

The designed metrics using textual data in combination with the structured data bring new insight to the Customer Experience which was previously hidden due to the lack of collecting textual data or because of their manual evaluation which does not allow discovering possible connections between data nor formulating complete insight. The storage of extracted information enables to monitor Customer Experience over time and find anomalies or patterns among customers, who can be further segmented.

The automatic text analytics approach leverages the manual evaluation of the content with the detection of the target objects (as defined in section 4.2) of the customer opinions, and the sentiment and emotions expressed about these target objects. The customer personality can also be predicted from the text. Personality is present along with emotions as latent constructs of Customer Experience throughout the customer's journey (see Figure 2.3: Customer Experience construct). The state in the journey is possible to track based on the designed metrics.

Current text analytics methods dealing with sentiment focus on the aggregated data regarded to products. Researchers then combine sentiment of the products and their aspects, but they are not able to reassign satisfaction to individual customers. The author retains the customer perspective with the relation of the target objects to customers. The requirements for text analytics methods to mine the Customer Experience elements of satisfaction, emotions and personality were defined in section 4.2.

The treatment design in Chapter 6 presented the actual deployment of text analytics methods in a case study based on customer reviews. The author combined different approaches according to the task performed: a lexicon-based approach for sentiment detection, rule-based approach for aspect detection, LDA for aspect category detection, deep learning for emotion detection, and clustering for personality detection. As the case study showed, the choice of methods is always individual and requires domain knowledge and many training data. Different tasks in text analytics were guided by CRISP-DM methodology.

RQ3) What is the implication of an enhanced Customer Experience Measurement model to Customer Experience Management?

The question RQ3 was answered in sections 5.9 and 6.5.1 during the design and evaluation of the implementation of the artefact. The managerial issues were defined in the results of the qualitative research in Chapter 2, where the barriers of achieving the full potential of analysing VoC within Customer Experience were defined (section 3.3.3). These barriers are eliminated with the designed artefact, as seen in section 5.9, and sections 6.3 and 6.5 which evaluated the treatment. In section 7.2 experts confirmed the benefits of the artefact. The justification of the needs for the model in section 5.2 reflects the real needs in Customer Experience Management. The concrete implications in a stakeholders' company are listed in section 6.5.1. Managing Customer Experience Measurement also has a direct impact on marketing activities. The author designed marketing actions for the stakeholders' company in section 6.2.6.3.

According to the general decision-making model (Šperková & Škola 2015), the primary purpose of Business Intelligence is data-based decision making, which in turn increases business performance. The same approach is emphasised in Customer Experience Management, where Customer Experience can be considered as part of a satisfaction-profit chain, as explained in section 2.5., and as part of a value creation chain. The metrics based on structured data are easily measurable, but the management of textual data determines how efficiently the company will deal with their customers in the future. The value for Customer represents their perception which cannot be calculated merely from structured data.

As the company's business grows, it loses touch with its customers, because the customer base grows and the complexity of understanding them increases. The artefact aims to solve this complexity with the sophisticated data-driven approach while maintaining a customer perspective through their customer journey. Using VoC data in Customer Experience helps to target marketing activities and even manage the subjectivity. If the company wants to contribute to customer retention, it must evaluate the interactions in a given context not only from the viewpoint of a marketing objective but also from the customer perspective. The proposed metrics then facilitate to answer different types of managerial questions: Who are the consumers who write negative feedback? What are their personality and emotions? How influential are they? How profitable are they? How do customers feel throughout different touchpoints of the overall customer journey experience? What is the impact of the Customer Experience on sales/margin/customer churn? What is the correlation between satisfaction score and customer churn/CLV?

The value and ROI from textual data can be considered similarly as in Business Continuity Management - as avoiding the potentially negative business impact due to absence of information caused by ignorance of the VoC. It can also happen that new, unexpected information from VoC needs to be addressed as a new project financed by the management of the company. Companies without the executive support of Customer Experience may be prevented from growing and building a competitive advantage in the market, or in the worst-case scenario, disrupt customer relationships. The risk arising from the ignorance of VoC can be sorted from dissatisfied customers, loud customers, rapidly rising costs for customer service, to customer churn, to breach of trust in the organisation, and customers who have more information than its employees.

Table 8.2: Research questions with the respective discussion chapters/sections

Research Question	**Chapter/Section**
RQ1) What is the current situation in the use of Voice of Customer within the Customer Experience Measurement?	Chapter 2 Customer Experience Measurement • Sections 2.2 - 2.7 Chapter 3 Qualitative Research on Use of Voice of Customer in Organisations • Sections 3.3 and 3.4 Chapter Summary
RQ2) How to incorporate Voice of Customer and its textual analytics into Customer Experience Measurement to further understand Customer Experience during the customer journey?	Chapter 4 Analysing the Content of VoC • Sections 4.2, 4.8 – 4.10 Chapter 5 Customer Experience Data Model Chapter 6 Validation of the Artefact with the TAR Method
RQ3) What are the implications of an enhanced Customer Experience Measurement model to Customer Experience Management?	Chapter 5 Customer Experience Data Model • Section 5.9 Chapter 6 Validation of the Artefact with the TAR Method • Section 6.5.1 • Section 6.5.2 Chapter 7 Validation of the Artefact with Expert Opinions • Section 7.2

8.3 Benefits of the Dissertation

According to design science research in information systems (Hevner et al. 2004), the dissertation contributes to both the academic research as well as the practice with several original implications. The main contribution of this thesis is the designed artefact of the

Customer Experience multidimensional data model and the proposed Customer Experience Measurement and its validation in practice. The main benefits of the designed artefact are listed in section 5.8., implications of the treatment implementation to Customer Experience Management are described in section 6.5.1.

As a **theoretical contribution** to academic research can also be considered:

1) Extensive literature review in Customer Experience, Voice of Customer and text analytics that bridges these three domains of academic research and brings some conceptualisation of the Customer Experience Measurement with use of textual data. The author closes the gap between the text analytics of VoC in marketing and in computer science by the integration of the knowledge from text analytics to Customer Experience in a concrete measurement model and by setting the relationship between the Customer Experience and Voice of Customer (VoC).

2) Customer Experience Construct. Approaches to Customer Experience Measurement and management varied in literature and practice, and there is not a unified method as constructs differ from monitored and measured elements. The author synthesised the existed practices into a unified Customer Experience Construct in section 2.4 (Figure 2.3) to measure overall Customer Experience. The construct represents a holistic conception of Customer Experience and serves as an initial building block for the design and construction of Customer Experience metrics and indicators (deliverable *D2*), and adjacent Customer Experience data model (deliverable *D1*). The model integrates the information from textual data with structured customer data.

3) Qualitative research on the use of VoC in Czech organisations operating in the internet environment brings some knowledge about measuring Customer Experience in praxis. The research detected six barriers to achieving the full potential of VoC analyses within Customer Experience (section 3.3.3). The barriers eliminated the designed artefact.

4) The author defined requirements to text analytics methods to mine Customer Experience elements of satisfaction, emotion and personality, which can serve as a guide for choice of appropriate methods.

5) The systematic review of LDA modifications in the author's article (Šperková 2018) examines the use of different LDA methods in text analytics of Customer Experience perceptual elements.

6) The architecture of the solution following the principles of BI where data are stored in relational tables enables easy integration of textual information within the structured environment.

7) The utilisation of text analytics methods based on Czech language datasets contributes to research in the Czech environment. Experimental detection of discrete emotions and personality traits from VoC had not been performed in the Czech academic research before. The rule-based approach with the use of PoS tags and dependency relations to detect aspects is the author's original solution which gained 98% accuracy on the labelled dataset.

8) Other academic articles (section 1.7) serve as confirmation of partial research related to the creation of this dissertation, published in international peer-reviewed journals and at international conferences.

Among the other **practical implications** belong:

9) The artefact represents a rigorous approach to the comprehensive measurement of overall Customer Experience at each stage of the customer journey for every touchpoint. The artefact shifts Customer Experience Measurement to a new level of customer insight which drives loyalty across different data sources which contribute to retention marketing efforts in companies.

10) The thesis presents the use of sophisticated data-driven and methodological approaches, mainly text analytics, not well established in marketing. The text analytics methods replace the hardly scalable and time-consuming manual processes of going through all responses and making conclusions from narrative stories in customer surveys or focus groups used in Customer Experience evaluation to extract the perceptual elements. The automatic evaluation of VoC from the Internet can provide valuable insights usable in isolation or in conjunction with traditional surveying that can affect the customers' opinions. The automatic detection of the elements boosts the process of measuring different metrics of Customer Experience. With a set of share-of-mind metrics, companies can now predict customer behaviour and future performance more precisely rather than using just a simple quantitative measurement of single metrics with transactional data and scale ratings. The inclusion of perceptual elements hidden in customer's written expressions in the form of opinions, emotions or personality enriches the evaluation of Customer Experience as this information cannot be found in transactional and other structured data.

11) Customer perspective offers a more detailed level of analysis, that provides direct one-to-one, customer-oriented, well-targeted approach replacing mass marketing conducted on aggregated data.

12) Deployment of the artefact to a real-world Czech environment. The treatment design and implementation represent an example of a specific application of text analytics into Customer Experience and the integration of the results to the relational data model used for further measurement.

13) Analysis of real-world e-commerce data in the form of customer reviews where the author utilises the concrete text analytics models following the requirements on mining the VoC elements stated in section 4.2.

14) The proposal of marketing actions and set of reports for Customer Experience monitoring.

8.4 Recommendations for Further Research

The area of Customer Experience research is multidisciplinary and dynamic, where many approaches can be applied. The advantage of the Customer Experience Measurement model is its extensibility. By following designed principles in this thesis, the model can be enhanced again. Future research should involve more data sources of customer interactions and embrace statistical and Machine Learning methods for modelling customer scenarios. The modelling of emotions and personality can combine the results of text analytics with the behaviour of customers on the Internet to get even more specific results. The development of the application based on the artefact that further enables collaboration, management of marketing activities, or alerting can also be a topic for further research.

The complexity of the customer journey and customer behaviour and the development of technologies require continuous adaptation of the management. Correspondingly, with new technology, the measurement can embrace listening techniques to recognise emotions from the voice, or video and image analytics to analyse mimics and gesture. With such amount of data will be necessary the transition to new technologies for processing and storage.

The Customer Experience model can be further enhanced with employee data. There is an evident link between employee satisfaction and customer satisfaction. A customer interacts with different employees with a different level of satisfaction, emotion and personality, thus may receive different service quality which influences his further experience. Employee's insight on customers complaints and issues and ways of solving these concerns can contribute to higher employees' engagement and work process improvements which directly impact the

Customer Experience with the company. In further research, employee satisfaction, emotions and personality may be an input to the Customer Experience Measurement model.

Regarding text analytics methods applied in this thesis, future research should perform the study, where the prediction abilities will be tested in comparison to traditional survey feedback metrics. If they perform as well as predictors, they could even replace the traditional surveys. Additionally, more case studies would confirm the sustainability of text analysis models across domains.

Machine Learning and text mining are limited in the cognitive depth they can achieve. The major problem of Machine Learning is producing results not understandable by humans. It is not enough to recognise customer sentiment without knowing why he has this emotion. Emotions can be expressed in an almost infinite number of ways, so building models or categorisation rules is problematic. Semantic models (appraisal taxonomies, ontologies, semantic networks) enable better reasoning about the meanings and emotions expressed in the text.

The future is in cognitive computing with the help of multilayer neural networks, also called deep learning or, in the case of text analytics, Reamy (2016) calls it "deep text". Vo et al. (2017) suggest combining deep learning with domain knowledge to improve the efficiency and accuracy of the systems. In future, the algorithms may be improved and replaced with these methods, which need many training data. The deep text integrates multiple techniques, rule-based methods and resources to a platform or infrastructure dealing with linguistic and cognitive complexity. To develop a framework enabling in-depth analytics will require significant work in developing taxonomies, textual analysis to capture all the variations in word usage and developing sufficiently sophisticated categorisation to provide useful insight. Such methods should also consider multi-language analytics as textual datasets can contain contributions in different languages. Future methods should be language-independent. Open-source frameworks for deep learning allow the computational capacity and scalability to perform such techniques. Future research may also consider new neuroscientific approaches.

Chapter 9

Conclusion

The dissertation reflects a move towards the business in a digital environment where content is generated by consumers of products and services. The dissertation stresses the importance of working with VoC, mainly in its textual form, as it can influence other customers. It can also uncover information which can significantly contribute to the definition of a customer. Such information cannot be easily obtained by manual analysis; therefore, this thesis proposes a data-driven automatic analysis of textual feedback.

Customer Experience plays a significant role in marketing management, as it pervades many processes dealing with customers. Customer Experience is based mainly on perceptual elements which emerge in customer behaviour and accompany the customer's entire journey. These elements are partly hidden in customers' written expressions. Therefore, the author of this thesis emphasises high value in textual VoC to measure Customer Experience as it contains information such as opinions, emotions, but also personality, which cannot be found in transactional and other structured data.

The author delivered the artefact of enhanced Customer Experience Measurement model (deliverable *D1*) with new metrics of customer satisfaction, emotion and personality traits (deliverable *D2*) with the use of text analytics methods (deliverable *D3*) by fulfilling all the stated objectives. Three research questions were also answered in the thesis. The artefact was validated by the treatment in the e-commerce environment on real-world data by Technical Action Research and experts' opinions. Dissertation accompanies an extensive review of the Customer Experience research, Voice of Customer research in marketing and text analytics approaches – three areas of concern.

Chapter 2 discussed the current approaches in Customer Experience, which are often focused on product/service experience and surveys evaluation. The chapter examines the role of VoC in Customer Experience. Quantitative methods of structured data analysis with individual metrics such as customer satisfaction predominate in VoC evaluation. In research, satisfaction represents dominant customer feedback for measuring perceptions. Text analytics of VoC in marketing research has not been adopted and focuses mostly on the simple evaluation of sentiment or manual evaluation of the content from customer surveys. The importance of customer's emotions and personality traits was stressed as these elements accompany the entire customer journey as primary drivers of customer behaviour. The different measurement models have also been discussed in terms of need a holistic conception of Customer Experience as a demonstration of experience through different elements, which originates in customer itself. The synthesis of existed practices into a unified Customer Experience Construct to measure overall Customer Experience is presented in the proposed Customer Experience construct (*D1a*).

Chapter 3 presented qualitative research conducted on a sample of Czech organisations operating in the B2C relationships within the Internet environment, while it was also published in (Šperková 2019). The research surveyed approaches to the analysis of VoC, textual data and Customer Experience. The researched companies found out to be immature in Customer Experience Measurement, and no comprehensive approach is utilised. The six barriers of full adoption of analysing VoC within Customer Experience mentioned in Czech companies were detected: 1) sharing VoC insight across the organisation, 2) struggle to prove financial results, 3) textual VoC is not profoundly analysed, 4) fragmented view of the customer and missing integration of data, 5) a missing action with individual customers, and 6) a missing formalisation of the processes.

Chapter 4 provided the introduction to text analytics with the focus on opinion mining and aspect detection techniques. The author defined the requirements for the text analytics methods for mining the elements of Customer Experience – satisfaction, emotions and personality. The chapter described the progress in the research of emotion mining and personality traits detection from textual data. Research in sentiment analysis in the Czech language was also discussed. In the last sections, the chapter focused on different approaches to the integration of VoC to Business Intelligence and CRISP-DM methodology as a framework for text analytics processes with references to the author's previous studies.

The research artefact in the form of the multidimensional Customer Experience Measurement data model (*D1*) with its measurement (*D2*) was proposed in Chapter 5. The model was designed to fulfil the data requirements on calculations and determinations of Customer Experience metrics according to the Customer Experience construct. The author proposed the set of metrics presenting the rigorous assessment of overall Customer Experience. These metrics serve for a periodical reporting at dashboards to improve Customer Experience Management. The data model is divided into two parts: the part for the storage of information from textual data and the analytical part. The architectural framework follows BI standards. The pre-processing phase precedes the textual stage and explains the capturing of opinion targets and syntactic dependencies. Next, the chapter described fact and dimension tables in the textual part of the model and relationship among them. In the end, the author discussed the benefits of the artefact.

Chapter 6 validated the textual part of the artefact with the Technical Action Research. The treatment in the real-world case in an e-commerce company evaluated the artefact's usefulness. The treatment design involved mining and integration of customer sentiment, emotions and personality with their opinion targets to the Customer Experience data model by application of text analytics methods (*D3*) based on stakeholders' criteria. The author analysed textual customer data in the form of customer reviews with a set of text analytics methods – a lexicon-based approach for customer sentiment, rule-based approach and Latent Dirichlet Allocation for aspects detection, deep-learning for emotions mining and clustering for personality detection following the CRISP-DM methodology. The rule-based approach of aspect detection resulted in 98% accuracy. The results of the methods met the stated criteria and were integrated with other structured data within the Customer Experience data model. Designed measurement involves a set of reports presented at three levels – company perspective, product perspective and customer perspective. The treatment design and its implementation to the stakeholders' environment were successfully evaluated by fulfilling their goals. In the end, implications of the treatment to Customer Experience Management as a part of implementation evaluation were discussed.

The validation of the artefact of Customer Experience data model and metrics for the Customer Experience Measurement with expert opinions were conducted in Chapter 7. Chapter 8 discussed the findings of the dissertation. The research questions answers were summarised, and the fulfilment of the objectives was evaluated. Lastly, recommendations for further research were proposed. Based on this chapter, the author can state that all the objectives of the thesis were fulfilled.

References

Abdolvand, N., Albadvi, A., & Aghdasi, M. (2015). Performance management using a value-based customer-centered model. *International Journal of Production Research*, *53*(18), pp. 5472-5483.

Abdul-Mageed, M., & Ungar, L. (2017). Emonet: Fine-grained emotion detection with gated recurrent neural networks. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)* (pp. 718-728).

Adalı, S., & Golbeck, J. (2014). Predicting personality with social behavior: a comparative study. *Social Network Analysis and Mining*, *4*(1), p. 159.

Alam, F., Stepanov, E. A., & Riccardi, G. (2013). Personality traits recognition on social network-facebook. *WCPR (ICWSM-13), Cambridge, MA, USA*.

Almossawi, M.M. (2015). The Impact of Word of Mouth (WOM) on the Bank Selection Decision of the Youth: A Case of Bahrain. *International Journal of Business and Management*, 10(4), pp.123–136.

Amichai-Hamburger, Y., & Vinitzky, G. (2010). Social network use and personality. *Computers in human behavior*, *26*(6), pp. 1289-1295.

Anderson, E. W. (1998). Customer satisfaction and word of mouth. *Journal of service research, 1*(1), pp. 5-17.

Archak, N., Ghose, A., & Ipeirotis, P. G. (2011). Deriving the pricing power of product features by mining consumer reviews. *Management Science, 57*(8), pp. 1485-1509.

Ashton, T., Evangelopoulos, N. & Prybutok, V.R. (2015). Quantitative quality control from qualitative data: control charts with latent semantic analysis. *Quality & Quantity*, 49(3), pp. 1081-1099.

Baars, H., & Kemper, H. G. (2008). Management support with structured and unstructured data—an integrated business intelligence framework. *Information Systems Management,* 25(2), pp. 132-148.

Bao, S., Xu, S., Zhang, L., Yan, R., Su, Z., Han, D., & Yu, Y. (2009, December). Joint emotion-topic modeling for social affective text mining. In *Ninth IEEE International Conference on Data Mining, 2009. ICDM'09*, pp. 699-704.

Bao, S., Xu, S., Zhang, L., Yan, R., Su, Z., Han, D., & Yu, Y. (2012). Mining social emotions from affective text. *IEEE transactions on knowledge and data engineering, 24*(9), pp. 1658-1670.

Berger, J., Sorensen, A. T., & Rasmussen, S. J. (2010). Positive effects of negative publicity: When negative reviews increase sales. *Marketing Science, 29*(5), pp. 815-827

Berger, P. D., Eechambadi, N., George, M., Lehmann, D. R., Rizley, R., & Venkatesan, R. (2006). From customer lifetime value to shareholder value: Theory, empirical evidence, and issues for future research. *Journal of Service Research, 9*(2), pp. 156-167.

Bhide, M. A., Gupta, A., Gupta, R., Roy, P., Mohania, M. K., & Ichhaporia, Z. (2007, June). Liptus: Associating structured and unstructured information in a banking environment. In *Proceedings of the 2007 ACM SIGMOD international conference on Management of data*, pp. 915-924.

Bickart, B. & Schindler, R.M. (2001). Internet forums as influential sources of consumer information. *Journal of Interactive Marketing*, 15(3), pp. 31-40.

Blei, D. M., & McAuliffe, J. D. (2008). Supervised topic models. In *Advances in neural information processing systems*, pp. 121-128.

Blitzer, J., Dredze, M., & Pereira, F. (2007, June). Biographies, bollywood, boom-boxes and blenders: Domain adaptation for sentiment classification. In *Proc. of the 45th Annual Meeting of the Association of Computational Linguistics, 7*, pp. 440-447.

Bolton, R. N. (1998). A Dynamic Model of the Duration of the Customer's Relationship with a Continuous Service Provider: The Role of Satisfaction. *Marketing Science, 17*(1), pp. 45–65.

Bolton, R. N., Lemon, K. N., & Verhoef, P. C. (2004). The theoretical underpinnings of customer asset management: A framework and propositions for future research. *Journal of the Academy of Marketing Science, 32*(3), pp. 271-292.

Bone, P. F. (1995). Word-of-mouth effects on short-term and long-term product judgments. *Journal of business research*, 32(3), pp. 213-223.

Brakus, J. J., Schmitt, B. H., & Zarantonello, L. (2009). Brand experience: what is it? How is it measured? Does it affect loyalty? *Journal of marketing, 73*(3), pp. 52-68.

Brychcín, T., & Habernal, I. (2013). Unsupervised improving of sentiment analysis using global target context. In *Proceedings of the international conference recent advances in natural language processing RANLP 2013* (pp. 122-128).

Brychcín, T., Konkol, M., & Steinberger, J. (2014). Uwb: Machine learning approach to aspect-based sentiment analysis. In *Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014)* (pp. 817-822).

BrightLocal (2016). *Local Consumer Review Survey*. [Online 2017-02-14]. Available on: <https://www.brightlocal.com/learn/local-consumer-review-survey/>.

Brody, S., & Elhadad, N. (2010, June). An unsupervised aspect-sentiment model for online reviews. In *Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics* (pp. 804-812). Association for Computational Linguistics.

Bronner, F. & de Hoog, R. (2010) Consumer-generated versus marketer-generated websites in consumer decision making. *International Journal of Market Research*, 52(2), pp. 231–248.

Buchanan, R. & Gilles, C., 1990. *Value Managed Relationship: The Key to Customer Retention and Profitability. European Management Journal,* 8(4).

Bügel, M. S., Verhoef, P. C., & Buunk, A. P. (2011). Customer intimacy and commitment to relationships with firms in five different sectors: Preliminary evidence. *Journal of Retailing and Consumer Services, 18*(4), pp. 247-258.

Buryan, J. (2013). Analýza sentimentu v příspěvcích na sociální síti Twitter. Bachelor Thesis. Brno, Masarykova univerzita, Fakulta informatiky.

Buttle, F., & Maklan S. (2015). *Customer relationship management: concepts and technologies*. Third edition. Routledge.

Casaló, L. V., Flavián, C., & Guinalíu, M. (2008). The role of satisfaction and website usability in developing customer loyalty and positive word-of-mouth in the e-banking services. *International Journal of Bank Marketing, 26*(6), pp. 399-417.

Castellanos, M., Wang, S., Dayal, U., & Gupta, C. (2010, June). SIE-OBI: a streaming information extraction platform for operational business intelligence. In *Proceedings of the 2010 ACM SIGMOD International Conference on Management of data*, pp. 1105-1110.

Červenec, R. (2011). *Rozpoznávání emocí v česky psaných textech*. Doctoral dissertation. Vysoké učení technické v Brně. Fakulta elektrotechniky a komunikačních technologií.

Chan, Y.Y.Y. & Ngai, E.W.T. (2011). Conceptualising electronic word of mouth activity: An input-process-output perspective. *Marketing Intelligence & Planning*, 29(5), pp.488–516.

Chapman, P., Clinton, J., Kerber, R., Khabaza, T., Reinartz, T., Shearer, C., & Wirth, R. (2000). CRISP-DM 1.0 Step-by-step data mining guide.

Chatterjee, P. (2001). Online reviews: do consumers use them? *Advances in Consumer Research*, 28(1), pp. 129–133.

Chau, M. & Xu, J. (2012). Business Intelligence in Blogs : Understanding Consumer Interactions and Communities. *MIS Quarterly*, 36(4), pp. 1189–1216.

Chaudhuri, S., & Dayal, U. (1997). An overview of data warehousing and OLAP technology. *ACM Sigmod record*, *26*(1), pp. 65-74.

Cheema, A. & Kaikati, A.M., 2010. The Effect of Need for Uniqueness on Word of Mouth. *Journal of Marketing Research*, 47(3), pp. 553–563.

Chen, S. C., & Lin, C. P. (2015). The impact of customer experience and perceived value on sustainable social relationship in blogs: An empirical study. *Technological Forecasting and Social Change, 96*, pp. 40-50.

Chen, J., Li, K., Zhu, J., & Chen, W. (2016). Warplda: a cache efficient o (1) algorithm for latent dirichlet allocation. *Proceedings of the VLDB Endowment*, *9*(10), pp. 744-755.

Chevalier, J.A. & Mayzlin, D. (2006) The effect of word of mouth on sales: online book reviews. *Journal of Marketing Research*, 43(3), pp. 345–354.

Choi, J. & Scott, J. (2013). Electronic Word of Mouth and Knowledge Sharing on Social Network Sites: A Social Capital Perspective. *Journal of theoretical and applied electronic commerce research*, 8(1), pp.11–12.

Choudhury, K. (2014). Service quality and word of mouth: a study of the banking sector. *International journal of bank marketing*, *32*(7), pp. 612-627.

Chung, W. (2009). Automatic summarization of customer reviews: An integrated approach. *AMCIS 2009 Proceedings*, p. 194.

Correa, T., Hinsley, A. W., & De Zuniga, H. G. (2010). Who interacts on the Web?: The intersection of users' personality and social media use. *Computers in Human Behavior*, *26*(2), pp. 247-253.

Court, D., Elzinga, D., Mulder, S., & Jørgen, O. V. (2009). The Consumer Decision Journey. *McKinsey Quarterly, 2009*(3), pp. 96–107.

Cronin Jr, J. J., & Taylor, S. A. (1992). Measuring service quality: a reexamination and extension. *The journal of marketing*, pp. 55-68.

Cronin Jr, J. J., Brady, M. K., & Hult, G. T. M. (2000). Assessing the effects of quality, value, and customer satisfaction on consumer behavioral intentions in service environments. *Journal of retailing*, *76*(2), pp. 193-218.

Dasgupta, S., & Ng, V. (2009, August). Mine the easy, classify the hard: a semi-supervised approach to automatic sentiment classification. In *Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP*, pp. 701-709.

Davidson, R. J., Sherer, K. R., & Goldsmith, H. H. (Eds.). (2009). *Handbook of affective sciences*. Oxford University Press.

Dave, K., Lawrence, S., & Pennock, D. M. (2003, May). Mining the peanut gallery: Opinion extraction and semantic classification of product reviews. In *Proceedings of the 12th international conference on World Wide Web*, pp. 519-528.

De Bruyn, A., & Lilien, G. L. (2008). A multi-stage model of word-of-mouth influence through viral marketing. *International Journal of Research in Marketing, 25*(3), pp. 151-163.

De Keyser, A., Lemon, K. N., Klaus, P., & Keiningham, T. L. (2015). A framework for understanding and managing the customer experience. *Marketing Science Institute working paper series*, *15*(121), pp. 1-48.

Dellarocas, C., Zhang, X. & Awad, N. (2007) Exploring the value of online product reviews in forecasting sales: the case of motion pictures. *Journal of Interactive Marketing*, 21, 4, pp. 23–45.

Dick, A. S., & Basu, K. (1994). Customer loyalty: toward an integrated conceptual framework. *Journal of the academy of marketing science*, *22*(2), pp. 99-113.

Dong, L. Y., Ji, S. J., Zhang, C. J., Zhang, Q., Chiu, D. W., Qiu, L. Q., & Li, D. (2018). An unsupervised topic-sentiment joint probabilistic model for detecting deceptive reviews. *Expert Systems with Applications*, *114*, pp. 210-223.

Duan, W., Cao, Q., Yu, Y., & Levy, S. (2013, January). Mining online user-generated content: using sentiment analysis technique to study hotel service quality. In *2013 46th Hawaii International Conference on System Sciences,* pp. 3119-3128.

Duhan, D. F., S. D. Johnson, J. B. Wilcox, & G. D. Harrell. (1997). Influences on consumer use of word-of-mouth recommendation sources. *Journal of the Academy of Marketing Science*, 25(4), pp. 283–295.

Dziurzynski, Lukasz, Edward Wadsworth, and Daniel McCarthy (2014). BTYD: Implementing Buy 'Til You Die Models. R package version 2.4. Retrieved from https://CRAN.R-project.org/package=BTYD.

East, R., Hammond, K., Harris, P., & Lomax, W. (2000). First-store loyalty and retention. *Journal of Marketing Management*, *16*(4), pp. 307-325.

Ekman, P. (1992). An argument for basic emotions. *Cognition & emotion*, *6*(3-4), pp. 169-200.

Ekman, P., Friesen, W. V., & Ellsworth, P. (1972). *Emotion in the Human Face: Guide-lines for Research and an Integration of Findings: Guidelines for Research and an Integration of Findings*. Pergamon.

Esuli, A., Sebastiani, F. (2006). Sentiwordnet: a publicly available lexical resource for opinion mining. In: *Proceedings of the 5th international conference on language resources and evaluation*.

Fader, P. (2012). *Customer centricity: Focus on the right customers for strategic advantage*. Wharton digital press.

Farhadloo, M., Patterson, R. A., & Rolland, E. (2016). Modeling customer satisfaction from unstructured data using a Bayesian approach. *Decision Support Systems*, *90*, pp. 1-11.

Farnadi, G., Zoghbi, S., Moens, M. F., & De Cock, M. (2013, July). Recognising personality traits using Facebook status updates. In *Proceedings of the workshop on computational personality recognition (WCPR13) at the 7th international AAAI conference on weblogs and social media (ICWSM13)*. AAAI.

Farris, P., Bendle, N. T., Pfeifer, P. E., & Reibstein, D. J. (2006). *Marketing metrics: Fifty+ metrics every marketer should know.*

Fathy, S., El-Haggar, N., & Haggag, M. H. (2017). A hybrid model for emotion detection from text. *International Journal of Information Retrieval Research (IJIRR)*, *7*(1), pp. 32-48.

Fellbaum, C.,(1998, ed.). *WordNet: An Electronic Lexical Database*. Cambridge, MA: MIT Press.

Feldman, R., & Sanger, J. (2007). *The text mining handbook: advanced approaches in analyzing unstructured data*. Cambridge university press.

Fousková, P. (2019). *Nové psychometrické přístupy k měření osobnosti-analýza digitálních stop a výsledků činnosti.* Bakalářská práce. Univerzita Karlova.

Fox, E. (2008). *Emotion science cognitive and neuroscientific approaches to understanding human emotions*. Palgrave Macmillan.

Gao, G. G., Greenwood, B. N., Agarwal, R., & McCullough, J. S. (2015). Vocal minority and silent majority: how do online ratings reflect population perceptions of quality?. *MIS Quarterly, 39*(3), pp. 565-589.

Gauri, D. K., Bhatnagar, A., & Rao, R. (2008). Role of word of mouth in online store loyalty. *Communications of the ACM*, *51*(3), pp. 89-91.

Gentile, C., Spiller, N., & Noci, G. (2007). How to sustain the customer experience: An overview of experience components that co-create value with the customer. *European Management Journal, 25*(5), pp. 395-410.

Ghose, A., Ipeirotis, P. G., & Li, B. (2012). Designing ranking systems for hotels on travel search engines by mining user-generated and crowdsourced content. *Marketing Science*, *31*(3), pp. 493-520.

Godes, D. & Mayzlin D. (2004). Using Online Conversations to Study Word-of-Mouth Communication. *Marketing Science*, 23(4), pp. 545–60.

Godes, D. and Mayzlin, D. (2009). Firm-created word-of-mouth communication: evidence from a field test. *Marketing Science*, 28(4), pp. 721-739.

Golbeck, J., Robles, C., Edmondson, M., & Turner, K. (2011, October). Predicting personality from twitter. In *Privacy, Security, Risk and Trust (PASSAT) and 2011 IEEE Third Inernational Conference on Social Computing (SocialCom), 2011 IEEE Third International Conference on* (pp. 149-156). IEEE.

Goldberg, L. R. (1990). An alternative" description of personality": the big-five factor structure. *Journal of personality and social psychology*, *59*(6), p. 1216.

Grewal, D., Levy, M., & Kumar, V. (2009). Customer experience management in retailing: An organizing framework. *Journal of Retailing, 85*(1), pp. 1-14.

Griffin, Abbie; Hauser, John R. (1993) The voice of the customer. *Marketing science*, 12(1), pp. 1-27.

Groeger, L., & Buttle, F. (2014). Word-of-mouth marketing: Towards an improved understanding of multi-generational campaign reach. *European Journal of Marketing, 48*(7/8), pp. 1186-1208.

Gruen, T. W., Osmonbekov, T., & Czaplewski, A. J. (2006). eWOM: The impact of customer-to-customer online know-how exchange on customer value and loyalty. *Journal of Business research, 59*(4), pp. 449-456.

Gu, B., Park, J., & Konana, P. (2012). Research note-the impact of external word-of-mouth sources on retailer sales of high-involvement products. *Information Systems Research*, 23(1), pp. 182-196.

Guo, W., & Deng, T. (2014, August). Topic mining for call centers based on LDA. In *2014 10th International Conference on Natural Computation (ICNC)*, pp. 839-844.

Gupta, S., Lehmann, D. R., & Stuart, J. A. (2004). Valuing customers. *Journal of marketing research*, *41*(1), pp. 7-18.

Gupta, S., & Lehmann, D. R. (2008). Models of customer value. In *Handbook of Marketing Decision Models* (pp. 255-290). Springer, Boston, MA.

Gupta, P., & Harris, J. (2010). How e-WOM recommendations influence product consideration and quality of choice: A motivation to process information perspective. *Journal of Business Research*, *63*(9), pp. 1041-1049.

Gupta, S., & Zeithaml, V. (2006). Customer metrics and their impact on financial performance. *Marketing science*, *25*(6), pp. 718-739.

Habernal, I., & Brychcín, T. (2013, September). Semantic spaces for sentiment analysis. In *International Conference on Text, Speech and Dialogue* (pp. 484-491). Springer, Berlin, Heidelberg.

Habernal, I., Ptáček, T., & Steinberger, J. (2013). Sentiment analysis in czech social media using supervised machine learning. In *Proceedings of the 4th workshop on computational approaches to subjectivity, sentiment and social media analysis*(pp. 65-74).

Habernal, I., Ptáček, T., & Steinberger, J. (2015). Reprint of “Supervised sentiment analysis in Czech social media”. *Information Processing & Management*, *51*(4), pp. 532-546.

Hajič, J., Bejček, E., Bémová, A., Buráňová, E., Hajičová, E., Havelka, J., Homola, P., Kárník, J., Kettnerová, V., Klyueva, N., Kolářová, V., Kučová, L., Lopatková, M., Mikulová, M., Mírovský, J., Nedoluzhko, A., Pajas, P., Panevová, J., Poláková, L., Rysová, M., Sgall, P., Spoustová, J., Straňák, P., Synková, P., Ševčíková, M., Štěpánek, J., Urešová, Z., Vidová Hladká, B., Zeman, D., Zikánová, Š. and Žabokrtský, Z. (2018). *Prague Dependency Treebank 3.5.* Institute of Formal and Applied Linguistics, LINDAT/CLARIN, Charles University, LINDAT/CLARIN PID: http://hdl.handle.net/11234/1-2621.

Han, X., & Niu, L. (2012). Word of Mouth Propagation in Online Social Networks. *JNW, 7*(10), pp. 1670-1676.

Haven, B., & Vittal, S. (2008). Measuring Engagement. Forrester Research Group. June 28.

Havíř, D. (2017). A comparison of the approaches to Customer Experience Analysis. *Economics and Business*, *31*(1), pp. 82-93.

Hayes, B. (2008). Measuring customer satisfaction and loyalty: survey design, use, and statistical analysis methods. ASQ Quality Press.

Hebbali, A. (2019, January). rfm: Recency, Frequency and Monetary Value Analysis. R package version 0.2.0. Retrieved from https://CRAN.R-project.org/package=rfm.

Hedegaard, S., & Simonsen, J. G. (2013, April). Extracting usability and user experience information from online user reviews. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems,* pp. 2089-2098.

Helm, S., & Schlei, J. (1998). Referral potential-potential referrals. An investigation into customers’ communication in service markets. In *Track 1 Market Relationships, Proceedings 27th EMAC Conference, Marketing Research and Practice*, pp. 41-56.

Hemmatian, F., & Sohrabi, M. K. (2017). A survey on classification techniques for opinion mining and sentiment analysis. *Artificial Intelligence Review*, pp. 1-51.

Hennig-Thurau, T., Gwinner, K.P., Walsh, G. and Gremler, D.D. (2004). Electronic word of mouth via consumer-opinion platforms: what motivates consumers to articulate themselves on the internet? *Journal of Interactive Marketing*, 18(1), pp. 38-52.

Hercig, T., Brychcín, T., Svoboda, L., & Konkol, M. (2016). Uwb at semeval-2016 task 5: Aspect based sentiment analysis. In *Proceedings of the 10th international workshop on semantic evaluation (SemEval-2016)* (pp. 342-349).

Hollebeek, L. D. (2011). Demystifying customer brand engagement: Exploring the loyalty nexus. *Journal of marketing management*, *27*(7-8), pp. 785-807.

Hu, M., & Liu, B. (2004, August). Mining and summarizing customer reviews. In *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*, pp. 168-177.

Hu, N., Koh, N. S., & Reddy, S. K. (2014). Ratings lead you to the product, reviews help you clinch it? The mediating role of online review sentiments on product sales. *Decision support systems*, *57*, pp. 42-53.

Hu, N., Pavlou, P.A. & Zhang, J. (2004). Can Online Reviews Reveal a Product ' s True Quality ? Empirical Findings and Analytical Modeling of Online Word-of-Mouth Communication. In: *Proceedings of the 7th ACM conference on Electronic commerce*. pp. 324–330.

Hu, N., Liu, L., & Zhang, J. J. (2008). Do online reviews affect product sales? The role of reviewer characteristics and temporal effects. *Information Technology and Management*, *9*(3), pp. 201-214.

Huang, J., Cheng, X. Q., Shen, H. W., Zhou, T., & Jin, X. (2012, February). Exploring social influence via posterior effect of word-of-mouth recommendations. In *Proceedings of the fifth ACM international conference on Web search and data mining* (pp. 573-582). ACM.

Huang, F., Zhang, S., Zhang, J., & Yu, G. (2017). Multimodal learning for topic sentiment analysis in microblogging. *Neurocomputing*, *253*, pp. 144-153.

Iacobelli, F., Gill, A. J., Nowson, S., & Oberlander, J. (2011). Large scale personality classification of bloggers. In *Affective computing and intelligent interaction* (pp. 568-577). Springer, Berlin, Heidelberg.

Inmon, W. H. (2002). *Building the Data Warehousing.*

Inmon, W. H., & Nesavich, A. (2007). *Tapping into unstructured data: integrating unstructured data and textual analytics into business intelligence*. Pearson Education.

Isaak, J., & Hanna, M. J. (2018). User Data Privacy: Facebook, Cambridge Analytica, and Privacy Protection. *Computer*, *51*(8), pp. 56-59.

Jain, R., Aagja, J., & Bagdare, S. (2017). Customer experience–a review and research agenda. *Journal of Service Theory and Practice*, *27*(3), pp. 642-662.

James, T. L., Calderon, E. D. V., & Cook, D. F. (2017). Exploring patient perceptions of healthcare service quality through analysis of unstructured feedback. *Expert Systems with Applications, 71*, pp. 479-492.

Jašek, P., Vraná, L., Šperková, L., Smutný, Z., & Kobulský, M. (2018, January). Modeling and Application of Customer Lifetime Value in Online Retail. In *Informatics*, *5*(1), p. 2. Multidisciplinary Digital Publishing Institute.

Jašek, P., Vraná, L., Šperková, L., Smutný, Z., & Kobulský, M. (2019). Comparative analysis of selected probabilistic customer lifetime value models in online shopping. *Journal of Business Economics and Management*, *20*(3), pp. 398-423.

Jašek, P., Vraná, L., Šperková, L., Smutný, Z., & Kobulský, M. (2019). Predictive Performance of Customer Lifetime Value Models in E-Commerce and the Use of Non-Financial Data. *Prague Economic Papers*, *28*(1), pp. 1-22.

Jindal N., Liu B. (2008) Opinion spam and analysis. In: Proceedings of the international conference on Web search and web data mining. ACM, New York,NY, USA, WSDM'08, pp 219–230.

Jindal, N., & Liu, B. (2006, August). Identifying comparative sentences in text documents. In *Proceedings of the 29th annual international ACM SIGIR conference on Research and development in information retrieval* (pp. 244-251). ACM.

Karlíček, M. (2013). *Základy marketingu. 1. ed. Praha: Grada, 2013, 255 p*. ISBN 978-80-247-4208-3.

Katz, E., & Lazarsfeld, P. F. (1955). *Personal Influence, The part played by people in the flow of mass communications*. Transaction Publishers.

Keiningham, T. L., Cooil, B., Andreassen, T. W., & Aksoy, L. (2007). *A longitudinal examination of net promoter and firm revenue growth. Journal of Marketing, 71*(3), pp. 39-51.

Khodadadi, P., Abdi, F., & Khalili-Damghani, K. (2016). An Integrated Model of Customer Experience, Perceived Value, Satisfaction, and Loyalty in Electronic Stores. *International Journal of Enterprise Information Systems (IJEIS), 12*(4), pp. 31-46.

Kimball, R., Ross, M., Mundy, J., & Thornthwaite, W. (2015). *The kimball group reader: Relentlessly practical tools for data warehousing and business intelligence remastered collection*. John Wiley & Sons.

Klaus, P. (2015). *Measuring customer experience: How to develop and execute the most profitable customer experience strategies*. Springer.

Klaus, P., & Maklan, S. (2012). EXQ: a multiple-item scale for assessing service experience. *Journal of Service Management*, *23*(1), pp. 5-33.

Klaus, P., & Maklan, S. (2013). Towards a Better Measure of Customer Experience. *International Journal of Market Research, 55*(2), pp. 227–246.

Kohavi, R., & Parekh, R. (2004, April). Visualizing RFM segmentation. In *Proceedings of the 2004 SIAM international conference on data mining* (pp. 391-399). Society for Industrial and Applied Mathematics.

Koppel, M., & Schler, J. (2006). The importance of neutral examples for learning sentiment. *Computational Intelligence, 22*(2), pp. 100-109.

Kotler, P., Keller, K. L. (2013). *Marketing management*. 4. ed. Praha: Grada, 2013, 814 p. ISBN 978-80-247-4150-5.

Konopık, M., Prazák, O., & Steinberger, D. (2017). Czech Dataset for Semantic Similarity and Relatedness. In *Proceedings of Recent Advances in Natural Language Processing*, pp. 401-406.

Kozinets, R. V., De Valck, K., Wojnicki, A. C., & Wilner, S. J. (2010). Networked narratives: Understanding word-of-mouth marketing in online communities. *Journal of marketing*, *74*(2), 71-89.

Kučera, D., Havigerová, J. M., Haviger, J., Cvrček, V., Komrsková, Z., Lukeš, D., & et al. (2018) CPACT (Computational Psycholinguistic Analysis of Czech Text, GA ČR 16-19087S), ale také perspektivy pro další výzkum v oblasti studia mezilidské verbální komunikace.

Kwantes, P. J., Derbentseva, N., Lam, Q., Vartanian, O., & Marmurek, H. H. (2016). Assessing the Big Five personality traits with latent semantic analysis. *Personality and Individual Differences, 102*, pp. 229-233.

Lakkaraju, H., Bhattacharyya, C., Bhattacharya, I., & Merugu, S. (2011, April). Exploiting coherence for the simultaneous discovery of latent facets and associated sentiments. In *Proceedings of the 2011 SIAM international conference on data mining*, pp. 498-509.

Lau, R. Y., Lai, C. C., Ma, J., & Li, Y. (2009). Automatic domain ontology extraction for context-sensitive opinion mining. *ICIS 2009 Proceedings*, pp. 35-53.

Larivière, B. (2008). Linking perceptual and behavioral customer metrics to multiperiod customer profitability: A comprehensive service-profit chain application. *Journal of Service Research*, *11*(1), pp. 3-21.

Lee, T. Y., & Bradlow, E. T. (2011). Automated marketing research using online customer reviews. *Journal of Marketing Research, 48*(5), pp. 881-894.

Lemke, F., Clark, M., & Wilson, H. (2011). Customer Experience quality: an exploration in business and consumer contexts using repertory grid technique. *Journal of the Academy of Marketing Science*, *39*(6), pp. 846-869.

Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing, 80*(6), pp. 69-96.

Lenc, L., & Hercig, T. (2016, September). Neural Networks for Sentiment Analysis in Czech. In *ITAT* (pp. 48-55).

Li, X., Wu, C., & Mai, F. (2019). The effect of online reviews on product sales: A joint sentiment-topic analysis. *Information & Management*, *56*(2), pp. 172-184.

Li, H., Pang, N., Guo, S., & Wang, H. (2007, December). Research on textual emotion recognition incorporating personality factor. In *Robotics and Biomimetics, 2007. ROBIO 2007. IEEE International Conference on* (pp. 2222-2227). IEEE.

Lin, W. H., Wilson, T., Wiebe, J., & Hauptmann, A. (2006, June). Which side are you on?: identifying perspectives at the document and sentence levels. In *Proceedings of the tenth conference on computational natural language learning* (pp. 109-116). Association for Computational Linguistics.

Lin, C. X., Ding, B., Han, J., Zhu, F., & Zhao, B. (2008, December). Text cube: Computing ir measures for multidimensional text database analysis. In *2008 Eighth IEEE International Conference on Data Mining*, pp. 905-910.

Lin, C., & He, Y. (2009, November). Joint sentiment/topic model for sentiment analysis. In *Proceedings of the 18th ACM conference on Information and knowledge management*, pp. 375-384.

Liu, B. (2012). Sentiment analysis and opinion mining. *Synthesis lectures on human language technologies, 5*(1), pp. 1-167.

Liu, B., Hu, M., & Cheng, J. (2005, May). Opinion observer: analyzing and comparing opinions on the web. In *Proceedings of the 14th international conference on World Wide Web*, pp. 342-351.

Liu, B. (2010). Sentiment Analysis and Subjectivity, Handbook of Natural Language Processing, Chemical Rubber Company (CRC) Press.

Liu, B. (2015). *Sentiment analysis: Mining opinions, sentiments, and emotions*. Cambridge University Press.

Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of marketing*, *70*(3), pp. 74-89.

Liu, Y., Wang, J., & Jiang, Y. (2016). PT-LDA: A latent variable model to predict personality traits of social network users. *Neurocomputing, 210*, pp. 155-163.

Lu, Y., Zhai, C., & Sundaresan, N. (2009, April). Rated aspect summarization of short comments. In *Proceedings of the 18th international conference on World Wide Web*, pp. 131-140.

Lü, L., Zhang, Y. C., Yeung, C. H., & Zhou, T. (2011). Leaders in social networks, the delicious case. *PloS one*, *6*(6), e21202.

Lukyanenko, R., Parsons, J., & Wiersma, Y. (2014). The IQ of the Crowd: Understanding and Improving Information Quality in Structured User-Generated Content. *Information Systems Research, 25*(4), pp. 669–689.

Mairesse, F., Walker, M. A., Mehl, M. R., & Moore, R. K. (2007). Using linguistic cues for the automatic recognition of personality in conversation and text. *Journal of artificial intelligence research*, *30*, pp. 457-500.

Marketing Science Institute. (2014). *Research Priorities 2014–2016*. Cambridge, MA: Marketing Science Institute. [Online.] Available at <http:// www.msi.org/uploads/files/MSI_RP14-16.pdf>.

Marketing Science Institute. (2016). *Research Priorities 2016–2018*. Cambridge, MA: Marketing Science Institute. [Online.] Available at <http://www.msi.org/ uploads/articles/MSI_RP16-18.pdf>.

Martin, J. R., & White, P. R. (2003). *The language of evaluation* (Vol. 2). Basingstoke: Palgrave Macmillan.

McCollister, C. (2016). *Predicting author traits through topic modeling of multilingual social media text* (Doctoral dissertation, University of Kansas).

McCrae, R. R., & John, O. P. (1992). An introduction to the five-factor model and its applications. *Journal of personality, 60*(2), pp. 175-215.

Medhat, W., Hassan, A. & Korashy, H., 2014. Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal*, 5(4), pp. 1093-1113.

Merton, R. K. (2008). *Focused interview*. Simon and Schuster.

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*.

Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems* (pp. 3111-3119).

Mishne, G. (2005, August). Experiments with mood classification in blog posts. In *Proceedings of ACM SIGIR 2005 workshop on stylistic analysis of text for information access*, 19, pp. 321-327.

Moghaddam, S., & Ester, M. (2012, October). On the design of LDA models for aspect-based opinion mining. In *Proceedings of the 21st ACM international conference on Information and knowledge management*, pp. 803-812.

Mohammad, S. M., & Turney, P. D. (2010, June). Emotions evoked by common words and phrases: Using Mechanical Turk to create an emotion lexicon. In *Proceedings of the NAACL HLT 2010 workshop on computational approaches to analysis and generation of emotion in text* (pp. 26-34). Association for Computational Linguistics.

Molnár, Z., Mildeová, S., Řezanková, H., Brixí, R., & Kalina, J. (2012). Pokročilé metody vědecké práce. *Praha: Profess Consulting*.

Montgomery, D. C. (2012). *Introduction to Statistical Quality Control, 7th Edition*.

Morgan, N. A., & Rego, L. L. (2006). The value of different customer satisfaction and loyalty metrics in predicting business performance. *Marketing Science, 25*(5), pp. 426-439.

Mukherjee, S., Basu, G., & Joshi, S. (2014, April). Joint author sentiment topic model. In *Proceedings of the 2014 SIAM International Conference on Data Mining* (pp. 370-378). Society for Industrial and Applied Mathematics.

Myers, M. D. (2013). *Qualitative research in business and management*. Sage.

Myers, I. B. (1962). The Myers-Briggs Type Indicator: Manual (1962).

Ng, R. T., Arocena, P. C., Barbosa, D., Carenini, G., Gomes, Jr, L., Jou, S., ... & Pottinger, R. A. (2013). Perspectives on Business Intelligence. *Synthesis Lectures on Data Management, 5*(1), pp. 1-163.

Netzer, O., Feldman, R., Goldenberg, J., & Fresko, M. (2012). Mine your own business: Market-structure surveillance through text mining. *Marketing Science, 31*(3), pp. 521-543.

Oberlander, J., & Nowson, S. (2006, July). Whose thumb is it anyway?: classifying author personality from weblog text. In *Proceedings of the COLING/ACL on Main conference poster sessions* (pp. 627-634). Association for Computational Linguistics.

Odekerken-Schröder, G., De Wulf, K., & Schumacher, P. (2003). Strengthening outcomes of retailer–consumer relationships: The dual impact of relationship marketing tactics and consumer personality. *Journal of business research*, *56*(3), pp. 177-190.

Pai, M. Y., Chu, H. C., Wang, S. C., & Chen, Y. M. (2013). Electronic word of mouth analysis for service experience. *Expert Systems with Applications, 40*(6), pp. 1993-2006.

Palese, B., & Piccoli, G. Online Reviews as a Measure of Service Quality. In: *2016 Pre-ICIS SIGDSA/IFIP WG8.3 Symposium*.

Pang, B., Lee, L., & Vaithyanathan, S. (2002, July). Thumbs up?: sentiment classification using machine learning techniques. In *Proceedings of the ACL-02 conference on Empirical methods in natural language processing,* 10, pp. 79-86. Association for Computational Linguistics.

Pang, B., & Lee, L. (2004, July). A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts. In *Proceedings of the 42nd annual meeting on Association for Computational Linguistics*, pp 271-278). Association for Computational Linguistics.

Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and trends in information retrieval, 2*(1-2), pp. 1-135.

Parasuraman, A., Zeithaml, V. & Berry, L. (1988). SERVQUAL: a multiple-item scale for measuring consumer perceptions of service quality, *Retailing: critical concepts*, 64(1), p. 140

Parasuraman, A., Zeithaml, V. A. & Berry, L. L. (1985). A conceptual model of service quality and its implications for future research, *Journal of Marketing*, pp. 41-50.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1994). Reassessment of expectations as a comparison standard in measuring service quality: implications for further research. *Journal of marketing*, *58*(1), pp. 111-124.

Park, D. H., & Lee, J. (2009). eWOM overload and its effect on consumer behavioral intention depending on consumer involvement. *Electronic Commerce Research and Applications, 7*(4), pp. 386-398.

Park, B. K., & Song, I. Y. (2012). Incorporating Text OLAP in Business Intelligence. In *Business Intelligence Applications and the Web: Models, Systems and Technologies*, pp. 77-101.

Park, D. H., Lee, J., & Han, I. (2007). The effect of on-line consumer reviews on consumer purchasing intention: The moderating role of involvement. *International journal of electronic commerce, 11*(4), pp. 125-148.

Parrott, W. G. (2001). *Emotions in social psychology: Essential readings*. Psychology Press.

Peng, W., Sun, T., Revankar, S., & Li, T. (2012). Mining the "voice of the customer" for business prioritization. *ACM Transactions on Intelligent Systems and Technology (TIST), 3*(2), p. 38.

Pennebaker, J.W., Boyd, R.L., Jordan, K., & Blackburn, K. (2015*). The development and psychometric properties of LIWC2015*. Austin, TX: University of Texas at Austin.

Pennebaker, J. W., & King, L. A. (1999). Linguistic styles: Language use as an individual difference. *Journal of personality and social psychology*, *77*(6), p. 1296.

Peralta, D. (2018, November 27). Customer experience guide: trends, strategies and examples for improving your customer experience in 2019. Hotjar. Retrieved from https://www.hotjar.com/blog/customer-experience.

Petre, M., Minocha, S., & Roberts, D. (2006). Usability beyond the website: an empirically-grounded e-commerce evaluation instrument for the total Customer Experience. *Behaviour & Information Technology*, *25*(2), pp. 189-203.

Pfeifer, P. E., Haskins, M. E., & Conroy, R. M. (2005). Customer lifetime value, customer profitability, and the treatment of acquisition spending. *Journal of managerial issues*, pp. 11-25.

Piryani, R., Madhavi, D., & Singh, V. K. (2017). Analytical mapping of opinion mining and sentiment analysis research during 2000–2015. *Information Processing & Management*, *53*(1), pp. 122-150.

Platzer, Michael (2016). BTYDplus: Probabilistic Models for Assessing and Predicting your Customer Base. R package version 1.0.1. Retrieved from https://CRAN.Rproject.org/package=BTYDplus.

Plutchik, R. (1980). Emotion: A Psychoevolutionary Synthesis, Harper and Row. *New York*.

Plutchik, R. (2001). The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice. *American scientist*, *89*(4), pp. 344-350.

Popescu, A. M., & Etzioni, O. (2007). Extracting product features and opinions from reviews. In *Natural language processing and text mining*, pp. 9-28.

Provost, F., & Kohavi, R. (1998). Glossary of terms. *Journal of Machine Learning*, *30*(2-3), pp. 271-274.

Ptáček, T., Habernal, I., & Hong, J. (2014). Sarcasm detection on czech and english twitter. In *Proceedings of COLING 2014, the 25th International Conference on Computational Linguistics: Technical Papers* (pp. 213-223).

Qu, Z., Zhang, H., & Li, H. (2008). Determinants of online merchant rating: Content analysis of consumer comments about Yahoo merchants. *Decision Support Systems, 46*(1), pp. 440-449.

Quan, X., Wang, Q., Zhang, Y., Si, L., & Wenyin, L. (2015). Latent discriminative models for social emotion detection with emotional dependency. *ACM Transactions on Information Systems (TOIS)*, *34*(1), p. 2.

Qiu, G., Liu, B., Bu, J., & Chen, C. (2011). Opinion word expansion and target extraction through double propagation. *Computational linguistics*, *37*(1), pp. 9-27.

Qiu, L., Lu, J., Ramsay, J., Yang, S., Qu, W., & Zhu, T. (2017). Personality expression in Chinese language use. *International Journal of Psychology*, *52*(6), pp. 463-472.

Rainardi, V. (2008). *Building a data warehouse: with examples in SQL Server*. John Wiley & Sons.

Rao, Y., Li, Q., Mao, X., & Wenyin, L. (2014). Sentiment topic models for social emotion mining. *Information Sciences*, *266*, pp. 90-100.

Rao, Y., Lei, J., Wenyin, L., Li, Q., & Chen, M. (2014). Building emotional dictionary for sentiment analysis of online news. *World Wide Web*, *17*(4), pp. 723-742.

Rao, Y., Li, Q., Wenyin, L., Wu, Q., & Quan, X. (2014). Affective topic model for social emotion detection. *Neural Networks*, *58*, pp. 29-37.

Rao, Y., Xie, H., Li, J., Jin, F., Wang, F. L., & Li, Q. (2016). Social emotion classification of short text via topic-level maximum entropy model. *Information & Management*, *53*(8), pp. 978-986.

Reamy, T. (2016). *Deep Text Using Text Analytics to Conquer Information Overload, Get Real Value from Social Media, and Add Big(ger) Text to Big Data.*

Reichheld, F. F. (2003). The one number you need to grow. *Harvard business review, 81*(12), pp. 46-55.

Reichheld, F. F., & Teal, T. (2001). *The loyalty effect: The hidden force behind growth, profits, and lasting value*. Harvard Business Press.

Richins, M. L. (1983). Negative word-of-mouth by dissatisfied consumers: A pilot study. *The journal of marketing*, pp. 68-78.

Richter, M., Straňák, P., & Rosen, A. (2012, December). *Korektor – A System for Contextual Spell-checking and Diacritics Completion* In Proceedings of the 24th International Conference on Computational Linguistics (Coling 2012), pp. 1-12, Mumbai, India, 2012.

Robson, K., Farshid, M., Bredican, J., Humphrey, S. (2013). Making sense of online consumer reviews a methodology. *International Journal of Market Research*, pp. 2–14.

Rud, O. P., 2001. *Data mining cookbook: modeling data for marketing, risk and customer relationship management*. New York: Wiley Computer Publishing, 367 p. ISBN 04-713-8564-6.

Selfhout, M., Burk, W., Branje, S., Denissen, J., Van Aken, M., & Meeus, W. (2010). Emerging late adolescent friendship networks and Big Five personality traits: A social network approach. *Journal of personality*, *78*(2), pp. 509-538.

Selivanov, D., & Wang, Q. (January 2018). text2vec: Modern text mining framework for R. R package version 0.5.1. Retrieved from https://CRAN. R-project. org/package= text2vec.

Scrucca, L. (2013). GA: a package for genetic algorithms in R. *Journal of Statistical Software*, *53*(4), pp. 1-37.

Shaheen, S., El-Hajj, W., Hajj, H., & Elbassuoni, S. (2014, December). Emotion recognition from text based on automatically generated rules. In *2014 IEEE International Conference on Data Mining Workshop* (pp. 383-392). IEEE.

Shaver, P., Schwartz, J., Kirson, D., & O'connor, C. (1987). Emotion knowledge: Further exploration of a prototype approach. *Journal of personality and social psychology*, *52*(6), p. 1061.

Schmidt-Subramanian, M. (2014). *The State of Voice of the Customer Programs, 2014: It's Time to Act*. Research report, Forrester Research.

Schmitt, B. H. (2010). *Customer experience management: A revolutionary approach to connecting with your customers.* John Wiley & Sons.

Schwartz, H. A., Eichstaedt, J. C., Kern, M. L., Dziurzynski, L., Ramones, S. M., Agrawal, M., ... & Ungar, L. H. (2013). Personality, gender, and age in the language of social media: The open-vocabulary approach. *PloS one*, *8*(9), e73791.

Sievert, C., & Shirley, K. (2014, June). LDAvis: A method for visualizing and interpreting topics. In *Proceedings of the workshop on interactive language learning, visualization, and interfaces* (pp. 63-70).

Song, B., Lee, C., Yoon, B., & Park, Y. (2016). Diagnosing service quality using customer reviews: an index approach based on sentiment and gap analyses. *Service Business*, *10*(4), pp. 775-798.

Steinberger, J., Brychcín, T., & Konkol, M. (2014). Aspect-level sentiment analysis in czech. In *Proceedings of the 5th workshop on computational approaches to subjectivity, sentiment and social media analysis* (pp. 24-30).

Steinberger, J., Lenkova, P., Kabadjov, M., Steinberger, R., & Van der Goot, E. (2011). Multilingual entity-centered sentiment analysis evaluated by parallel corpora. In *Proceedings of the International Conference Recent Advances in Natural Language Processing 2011* (pp. 770-775).

Steinberger, J., Lenkova, P., Ebrahim, M., Ehrmann, M., Hurriyetoglu, A., Kabadjov, M., ... & Vázquez, S. (2011, June). Creating sentiment dictionaries via triangulation. In *Proceedings of the 2nd workshop on computational approaches to subjectivity and sentiment analysis* (pp. 28-36). Association for Computational Linguistics.

Stirling, M. (2000). Customer value management. *Journal of Targeting, Measurement and Analysis for Marketing*, *9*(2), pp. 174-184.

Storbacka, K., & Lehtinen, J. (2002). *Řízení vztahů se zákazníky*.

Straka, M., & Straková, J. (2017). Tokenizing, pos tagging, lemmatizing and parsing ud 2.0 with udpipe. *Proceedings of the CoNLL 2017 Shared Task: Multilingual Parsing from Raw Text to Universal Dependencies*, pp. 88-99.

Straka, M., & Straková, J. (2018). Universal Dependencies 2.3 Models for UDPipe (2018-11-15), LINDAT/CLARIN digital library at the Institute of Formal and Applied Linguistics (ÚFAL), Faculty of Mathematics and Physics, Charles University, http://hdl.handle.net/11234/1-2898.

Strapparava, C., & Mihalcea, R. (2008, March). Learning to identify emotions in text. In *Proceedings of the 2008 ACM symposium on Applied computing*, pp. 1556-1560.

Sumner, C., Byers, A., Boochever, R., & Park, G. J. (2012, December). Predicting dark triad personality traits from twitter usage and a linguistic analysis of tweets. In *Machine learning and applications (icmla), 2012 11th international conference on*(Vol. 2, pp. 386-393). IEEE.

Sun, H. (2013). Moderating Role of Online Word of Mouth on Website Attributes and Consumer Trust in E-commerce Environment. *Journal of Applied Sciences*, 13, pp. 2316-2320.

Sun, S., Luo, C., & Chen, J. (2017). A review of natural language processing techniques for opinion mining systems. *Information Fusion, 36*, pp. 10-25.

Šperková, L. (2014). Word of Mouth analysis on facebook in banking. In: *Marketing identity*. Smolenice, pp. 236-252. Trnava: Univerzita sv. Cyrila a Metoda v Trnava.

Šperková, L. (2014). Analýza nestrukturovaných dat z bankovních stránek na sociální síti Facebook. *Acta Informatica Pragensia*, *3*(2), pp. 154-167.

Šperková, L. (2016). Využití analýz obsahu Voice of Customer v marketingu. In: *Sborník prací účastníků vědeckého semináře doktorského* studia *FIS VŠE v Praze*, Praha, pp. 42-52.

Šperková, L. (2018). Review of Latent Dirichlet Allocation Methods Usable in Voice of Customer Analysis. *Acta Informatica Pragensia, 7*(2), pp.152-165.

Šperková, L. (2019). Qualitative Research on Use of Voice of Customer in Czech Organisations. *Journal of Systems Integration*, *10*(2), pp. 9-18.

Šperková, L.,& Feuerlicht, G. (2017). Application of CRISP-DM to Voice of Customer and BI integration, In *Progress in Intelligent Computing and Applications (PICA)*, *5*(1), pp. 7–13.

Šperková, L., Vencovský, F., & Bruckner, T. (2015). How to Measure Quality of Service Using Unstructured Data Analysis: A General Method Design. *Journal of systems integration*, *6*(4), pp. 3–16.

Šperková, L., & Škola, P. (2015). Design of Metrics for e-Word-of-Mouth Evaluation From Unstructured Data for Banking Sector. In: *16th European Conference on Knowledge Management*, Udine, pp. 717-725. Academic Conferences International Limited.

Šperková, L., & Škola, P. (2015). E-WoM Integration to the Decision-Making Process in Bank Based on Business Intelligence. *Proceedings of the 23nd Interdisciplinary Information Management Talks*, pp. 207-216. Springer.

Šperková, L., Škola, P., & Bruckner, T. (2015). Evaluation of e-Word-of-Mouth through Business Intelligence processes in banking domain. *Journal of Intelligence Studies in Business, 5*(2)., pp. 36-47.

Tamchyna, A., Fiala, O., & Veselovská, K. (2015). Czech Aspect-Based Sentiment Analysis: A New Dataset and Preliminary Results. In *ITAT* (pp. 95-99).

Tamchyna, A., & Veselovská, K. (2016). UFAL at semeval-2016 task 5: recurrent neural networks for sentence classification. In *Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016)* (pp. 367-371).

Titov, I., & McDonald, R. (2008, April). Modeling online reviews with multi-grain topic models. In *Proceedings of the 17th international conference on World Wide Web*, pp. 111-120.

Titov, I., & McDonald, R. T. (2008, June). A Joint Model of Text and Aspect Ratings for Sentiment Summarization. In *ACL*, 8, pp. 308-316.

Tsang, A. & Prendergast, G. (2009) Is a 'star' worth a thousand words? European Journal of Marketing, 43, pp. 1269–1280.

Tsiptsis, K. K., & Chorianopoulos, A. (2011). *Data mining techniques in CRM: inside customer segmentation*. John Wiley & Sons.

Tsytsarau, M., & Palpanas, T. (2012). Survey on mining subjective data on the web. *Data Mining and Knowledge Discovery*, *24*(3), pp. 478-514.

Turney, P. D. (2002, July). Thumbs up or thumbs down?: semantic orientation applied to unsupervised classification of reviews. In *Proceedings of the 40th annual meeting on association for computational linguistics*, pp. 417-424.

Vaishnavi, V. K., & Kuechler, W. (2015). *Design science research methods and patterns: innovating information and communication technology*. Crc Press.

Vencovský, F. (2018). *E-service Quality Measurement From Customers' Point of View*. Doctoral Dissertation. University of Economics, Prague.

Vencovský, F., Bruckner, T., & Šperková, L. (2016, July). Customer Feedback Analysis: Case of E-banking Service. In *3rd European Conference on Social M di R h Media Research EM Normandie, Caen, France* (p. 404).

Vencovský, F., & Šperková, L. (2015). IT Service Quality Model: Evaluation of Quality In Use. In: *16th European Conference on Knowledge Management*. Udine, pp. 821-827. Academic Conferences International Limited.

Verhoef, P. C. (2003). Understanding the effect of customer relationship management efforts on customer retention and customer share development. *Journal of Marketing, 67*(4), pp. 30-45.

Verhoef, P. C., Lemon, K. N., Parasuraman, A., Roggeveen, A., Tsiros, M., & Schlesinger, L. A. (2009). Customer experience creation: Determinants, dynamics and management strategies. *Journal of retailing*, *85*(1), pp. 31-41.

Verhoef, P. C., & Lemon, K. N. (2016). Advances in customer value management. *Handbook of Research in Relationship Marketing*, pp. 75-103.

Veselovská, K. (2010). *Členská negace a způsob jejího vyjadřování v současné češtině*. Master's thesis, Univerzita Karlova.

Veselovská, K. (2012, June). Sentence-level sentiment analysis in Czech. In *Proceedings of the 2nd International Conference on Web Intelligence, Mining and Semantics* (p. 65). ACM.

Veselovská, K. (2017). *Sentiment Analysis in Czech*. Ústav formální a aplikované lingvistiky.

Veselovská, K., Bojar, O. (2013). *Czech SubLex 1.0*, LINDAT/CLARIN digital library at the Institute of Formal and Applied Linguistics (ÚFAL), Faculty of Mathematics and Physics, Charles University, http://hdl.handle.net/11858/00-097C-0000-0022-FF60-B.

Veselovská, K., & Tamchyna, A. (2014). ÚFAL: Using hand-crafted rules in aspect based sentiment analysis on parsed data. In *Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014)* (pp. 694-698).

Wald, R., Khoshgoftaar, T. M., Napolitano, A., & Sumner, C. (2012, December). Using Twitter content to predict psychopathy. In *Machine Learning and Applications (ICMLA), 2012 11th International Conference on* (Vol. 2, pp. 394-401). IEEE.

Walther, J. B., Loh, T., & Granka, L. (2005). Let me count the ways: The interchange of verbal and nonverbal cues in computer-mediated and face-to-face affinity. *Journal of language and social psychology*, *24*(1), pp. 36-65.

Wang, H., Lu, Y., & Zhai, C. (2010, July). Latent aspect rating analysis on review text data: a rating regression approach. In *Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining*, pp. 783-792.

Wheat, R. D., & Morrison, D. G. (1990). Estimating purchase regularity with two interpurchase times. *Journal of Marketing Research*, *27*(1), pp. 87-93.

Whelan, S., & Davies, G. (2006). Profiling consumers of own brands and national brands using human personality. *Journal of Retailing and Consumer Services*, *13*(6), pp. 393-402.

Wieringa R. (2014). *Design science methodology for information systems and software engineering.*

Wieringa, R., & Morali, A. (2012, May). Technical action research as a validation method in information systems design science. In *International Conference on Design Science Research in Information Systems*, pp. 220-238. Springer Berlin Heidelberg.

Wijffels, J. (2019, July). udpipe: Tokenization, Parts of Speech Tagging, Lemmatization and Dependency Parsing with the'UDPipe''NLP'Toolkit. R package version 0.8.3. Retrieved from https://CRAN.R-project.org/package=udpipe.

Winer, R. S. (2009). New communications approaches in marketing: Issues and research directions. *Journal of Interactive Marketing, 23*(2), pp. 108-117.

Wu, W., & Zheng, R. (2012, August). The impact of word-of-mouth on book sales: review, blog or tweet?. In *Proceedings of the 14th Annual International Conference on Electronic Commerce* (pp. 74-75). ACM.

Yaakub, M. R. (2015). *Integration of opinion into customer analysis model*. PhD thesis. Queensland University of Technology.

Yaakub, M. R., Li, Y., Algarni, A., & Peng, B. (2012, December). Integration of opinion into customer analysis model. In *Proceedings of the The 2012 IEEE/WIC/ACM International Joint Conferences on Web Intelligence and Intelligent Agent Technology-Volume 03* (pp. 164-168). IEEE Computer Society.

Yadollahi, A., Shahraki, A. G., & Zaiane, O. R. (2017). Current state of text sentiment analysis from opinion to emotion mining. *ACM Computing Surveys (CSUR)*, *50*(2), p. 25.

Yang, C. C., Tang, X., Wong, Y. C., & Wei, C. P. (2010). Understanding online consumer review opinions with sentiment analysis using machine learning. *Pacific Asia Journal of the Association for Information Systems*, *2*(3).

Yim, C. K., Tse, D. K., & Chan, K. W. (2008). Strengthening customer loyalty through intimacy and passion: Roles of customer–firm affection and customer–staff relationships in services. *Journal of marketing research, 45*(6), pp. 741-756.

Yin, R. K. (2009). Case study research: Design and methods 4th ed.

Youyou, W., Kosinski, M., & Stillwell, D. (2015). Computer-based personality judgments are more accurate than those made by humans. *Proceedings of the National Academy of Sciences*, *112*(4), pp. 1036-1040.

Zaki, M., & Neely, A. (2019). Customer Experience Analytics: Dynamic Customer-Centric Model. In *Handbook of Service Science, Volume II* (pp. 207-233). Springer, Cham.

Zhang, R., & Tran, T. (2011). A helpfulness modeling framework for electronic word-of-mouth on consumer opinion platforms. *ACM Transactions on Intelligent Systems and Technology (TIST)*, *2*(3), p. 23.

Zhang, X., Yu, Y., Li, H., & Lin, Z. (2016). Sentimental interplay between structured and unstructured user-generated contents: An empirical study on online hotel reviews. *Online Information Review, 40*(1), pp. 119-145.

Zhang, L., Wang, S., & Liu, B. (2018). Deep learning for sentiment analysis: A survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, e1253.

Appendix A

The appendix introduces the original list of formal questionnaire survey inquiries and its answers subsequently used in a focused interview with selected organisations in Chapter 3. The appendix also contains the cover letter intended to distribute through analytical websites and professional social network LinkedIn. The questionnaire contained ten questions about the use of VoC in measuring share-of-mind customer metrics and six questions regarding the organisation.

Cover letter

The questionnaire started with a definition and a brief description as follow:

Voice of Customer is content generated by users which can be collected from various sources such as online customer reviews, forums, social networks, but also direct company's channels like emails, calls to call centres or customer surveys. It can be in the form of structured data like scales (stars) in reviews or check answers in conducted surveys, but mostly is in the unstructured, free textual form.

This is a survey of collecting, analysing and using Voice of Customer in organisations closely connected to Text Analytics.

Please respond only if you are a marketer, consultant, analyst or a manager or executive of staff in those roles. Researchers and developers who apply technologies/solutions to data analysis problems are also welcoming to respond, but the survey is not intended otherwise for solution providers.

There are 16 questions. The survey should take you 5-10 minutes to complete.

I will be preparing a free report with my findings. Thanks for participating.

Lucie Sperkova, lucie.sperkova@vse.cz

The introduction ended with the text:

Privacy statement: This survey asks for the name of the organisation you work for, which will be used only in an effort to detect bogus responses. It is your choice whether to provide your name, company, and contact information. That information will not be linked to your survey responses.

Survey Questions

Part I – Use of Voice of Customer in Organisations

1) Does your organisation measure and evaluate in some way these "soft" customer metrics? (multi-choice)

    a) Customer satisfaction
    b) Customer loyalty
    c) Customer engagement
    d) Customer behaviour
    e) Customer sentiment
    f) Customer emotions
    g) Customer personality traits
    h) Customer experience
    i) We do not measure soft customer metrics

2) Are these measures parts of a more comprehensive view of the customer?

    a) No, we only do ad hoc reporting
    b) Yes, we monitor customer metrics periodically with complex dashboards

3) Is your organisation engaged in evaluating the VoC (even in structured form - e.g. product ratings, structured surveys)? (multi-choice)

    a) No
    b) Yes, to become more customer-focused
    c) Yes, to better satisfy customer needs and desires
    d) Yes, to identify opportunities for innovation
    e) Yes, for purposes of planning products and services
    f) Yes, for marketing purposes
    g) Yes, for making work system and work process improvements
    h) Yes, for developing new business opportunities
    i) Yes, for measuring comprehensive Customer Experience
    j) Other

4) How does your organisation measure these metrics? (open-ended question)

5) Does your organisation collect customers' textual data - VoC in textual form? (if not, skip the rest of the questions and go to next section)

    a) No

b) Yes, we collect them but do not analyse

c) Yes, we collect them and further analyse

6) From which sources does your organisation collect textual VoC? (multi-choice)

a) Blog

b) Microblog (Twitter)

c) Social networks (Facebook)

d) Customer/market surveys

e) Online forums

f) Online reviews

g) Email

h) Contact centres and transcripts

i) Chat

j) Website feedback

k) Other

7) Your organisation analyses customer textual data for the purposes of: (multi-choice)

a) Measuring customer satisfaction and loyalty

b) Measuring Customer Experience

c) Determination of customer's personality

d) Detecting customer emotions

e) Detecting customer sentiment

f) Detecting customer expectations, needs and requirements

g) Other

8) Which tools does your organisation use to analyse textual data? (multi-choice)

a) We analyse manually without any automated approach

b) We bought a specialized software package

c) We do text analytics ourselves with our tools or within our solution

d) We use open-source and free software (Knime, Gensim library, NLTK, RapidMiner etc.)

e) Other

9) When analysing text, do you extract or analyse (for every answer choose the measuring scale: do not analyse - currently analyse - expect to analyse)

a) Topics and themes

b) Sentiment, opinions, attitudes, emotions, perceptions, intents

c) Relationships, facts

d) Named entities - companies, people, locations, ...

e) Concepts (abstract groups of entities)

f) Metadata (document author, publication date, title, ...)

g) Other entities (email, phone number, product number)

h) Semantic annotations

i) Events

10) Any comments you want to share

Part II - Information about the organisation

11) Location of the company (city)

12) How long has your organisation been in business?

a) 0 - 2 years
b) 3 - 5 years
c) 6 - 10 years
d) More than 10 years

13) In what industry the organisation operates?

a) Retail and e-commerce
b) Finance and banking
c) Energy and utility
d) Telecommunications
e) Healthcare
f) Public sector
g) Higher education
h) Manufacturing and Consumer Packaged Goods
i) Engineering and construction
j) Other

14) How many employees does the organisation have?

a) Less than 10
b) Between 10 and 50
c) Between 50 and 250
d) Between 250 and 1000

e) More than 1000

15) How many customers does the organisation have?

a) Less than 1000
b) Between 1000 and 10 000
c) Tens of thousands
d) Hundreds of thousands or more

16) Name of the organisation, your role and email (optional)

Appendix B

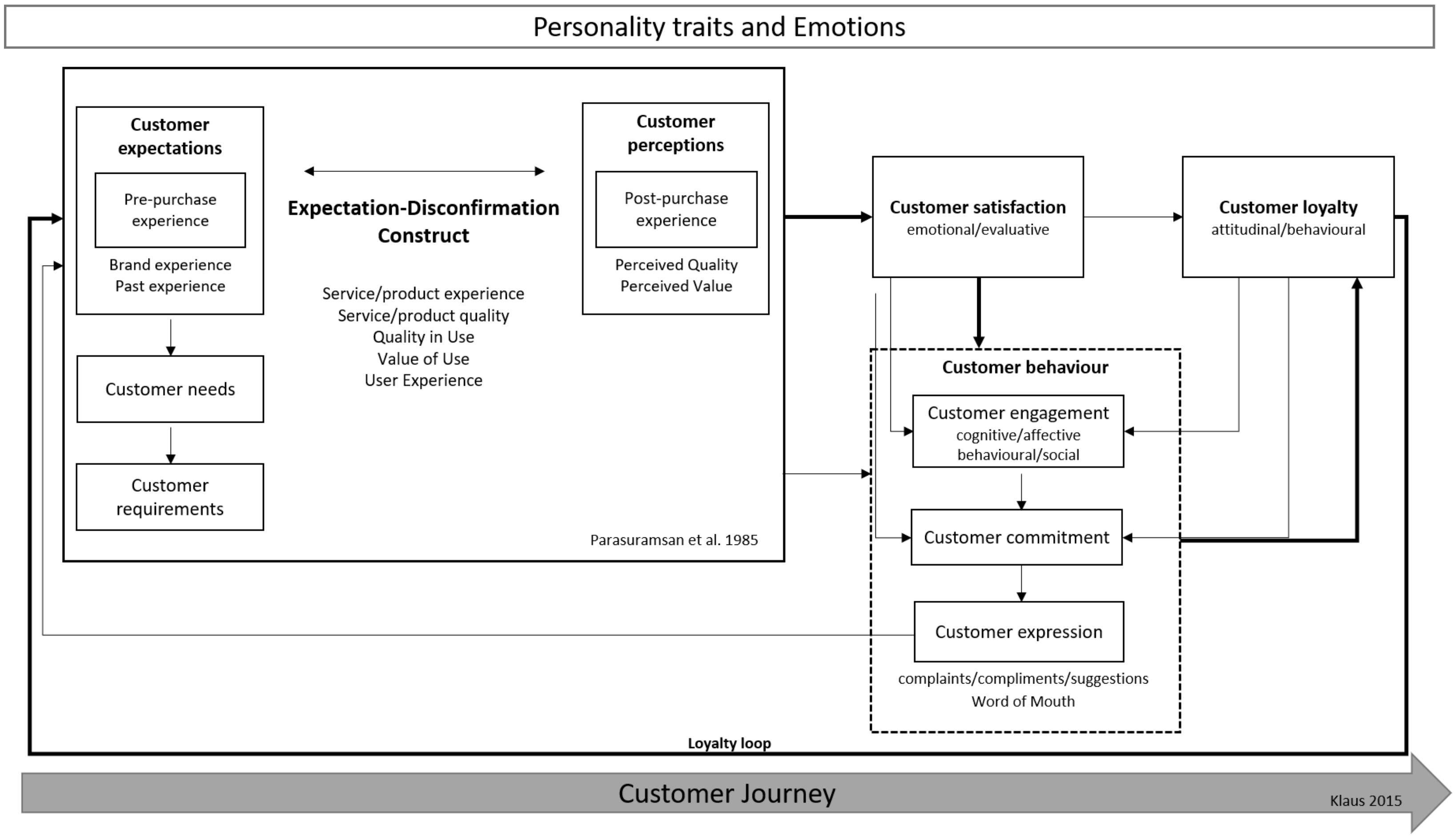

Figure B.1: Customer Experience construct

Appendix C

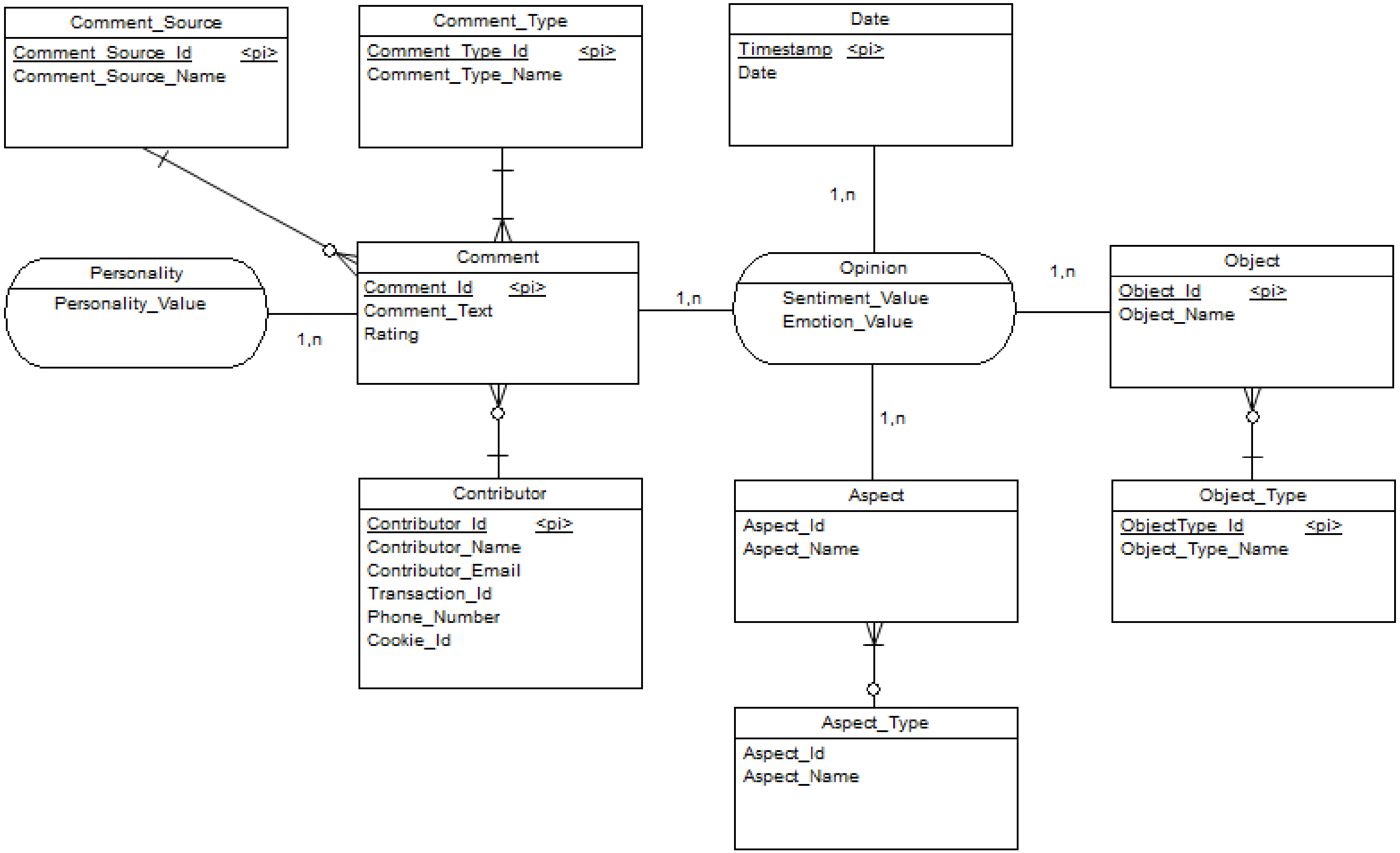

Figure C.2: Conceptual model of the textual stage

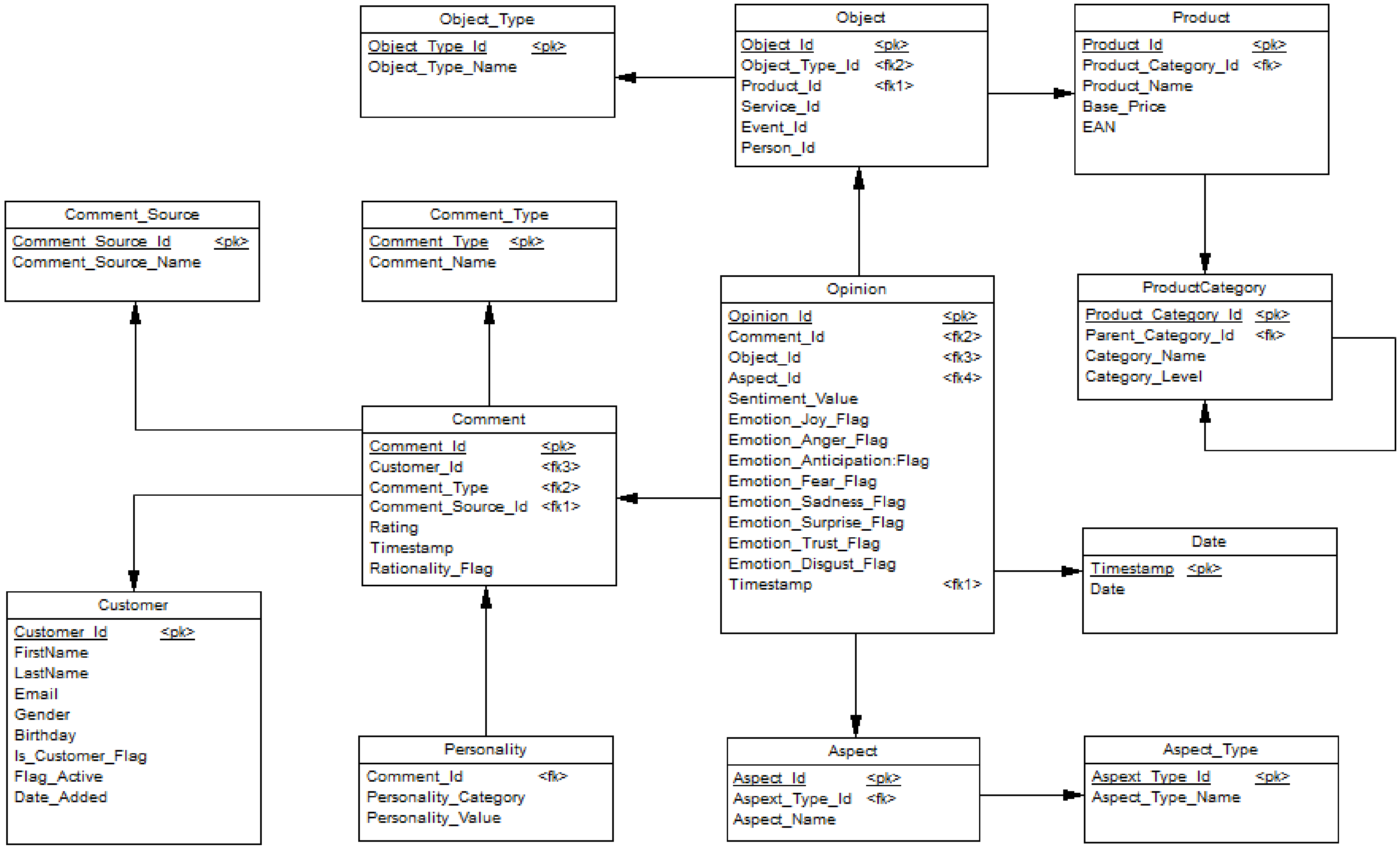

Figure C.3: Physical model of the textual stage

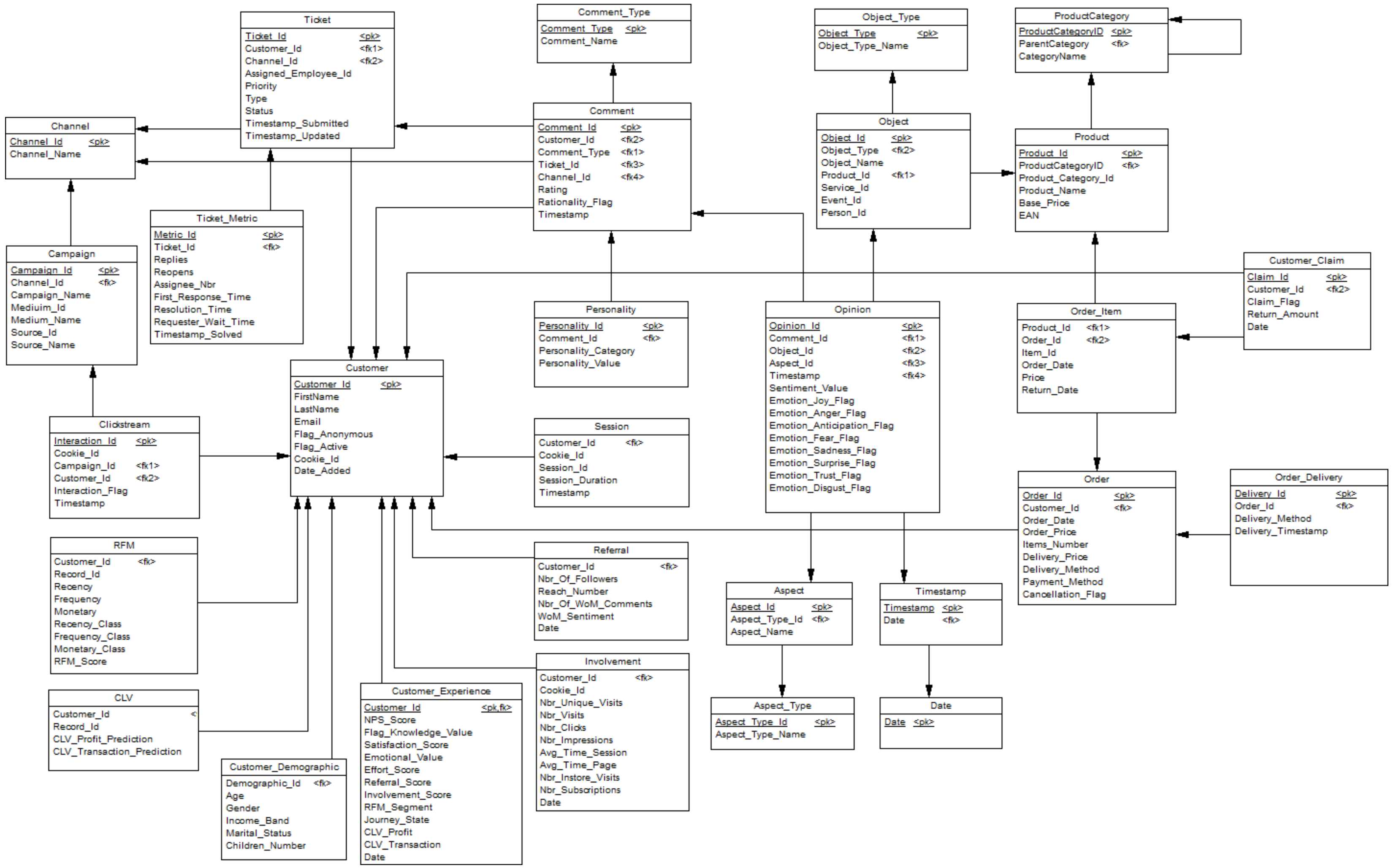

Figure C.4: Physical model of the Analytical stage of the Customer Experience Measurement model

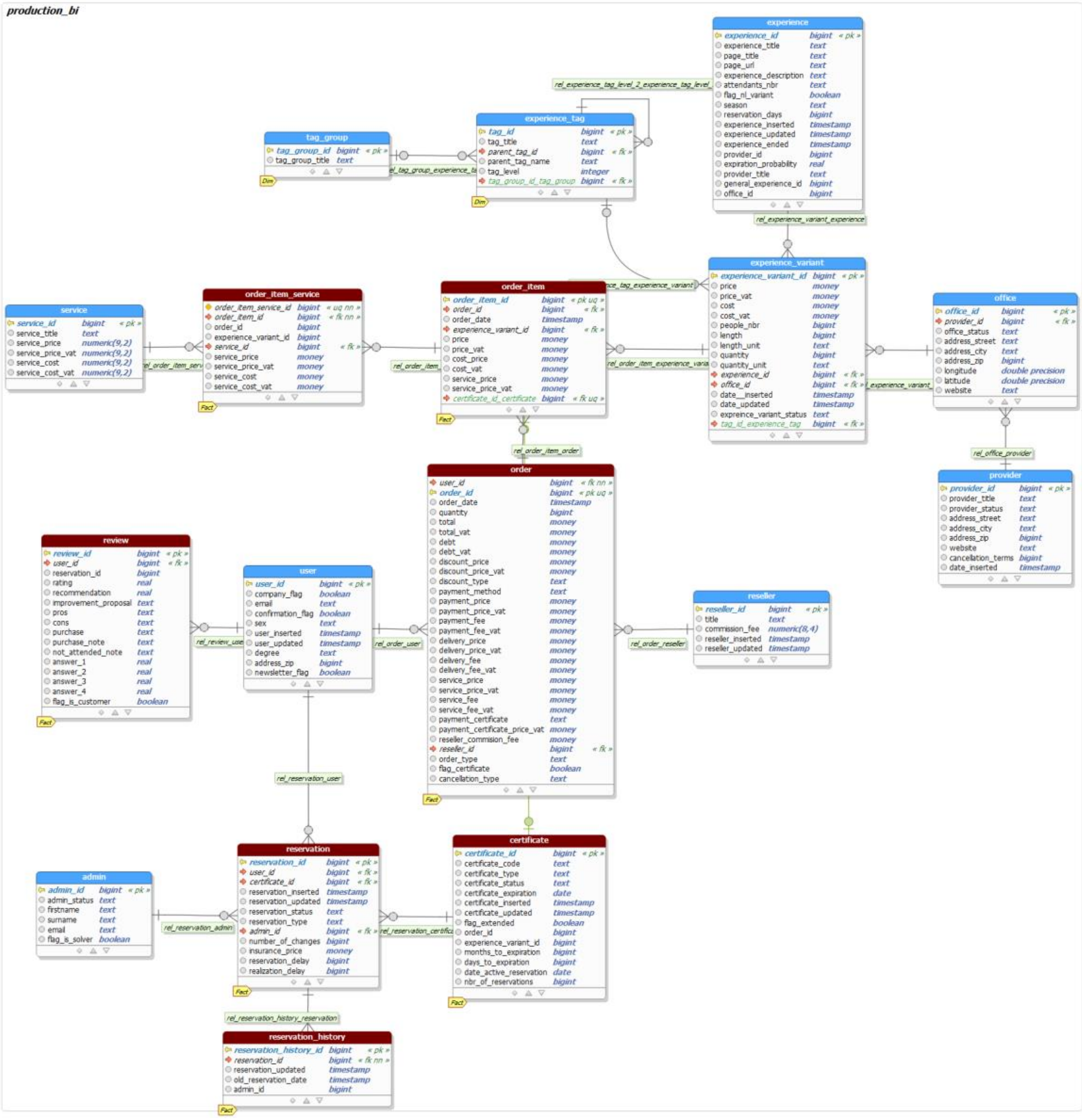

Figure C.5: Data warehouse of the company's production system created by the author[77]

[77] The model was generated with the PostgreSQL Database Modeler.