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L'INTELLIGENCE CLIENT À L'ÈRE DES DONNÉES MASSIVES : UN MODÈLE POUR LES PME/PMO DU SECTEUR CULTUREL

CUSTOMER INTELLIGENCE IN THE AGE OF BIG DATA: A MODEL FOR SMES/SMOS IN THE CULTURAL SECTOR

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L'intelligence client à l'ère des données massives : un modèle pour les PME/PMO du secteur culturel

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SUMMARY

The age of big data has sparked a growing interest of enterprises in adopting customer intelligence to survive and thrive in the fierce competition. Customer intelligence, which is defined as insights and knowledge acquired by business analytics from user-generated data on digital platforms, becomes a valuable means for supporting data-driven decisions in marketing. Literature has specifically addressed the superiority of customer intelligence in today's economy and the opportunities for enterprises to take advantage of it for marketing benefits. The application of customer intelligence offers win-win solutions for both enterprises and customers. On the one hand, enterprises can improve their marketing and financial performance; on the other hand, customers can increase their satisfaction and experience with products/services.

Regardless of promising opportunities, customer intelligence also brings enormous challenges for enterprises, particularly small and medium-sized enterprises and organizations (SMEs/SMOs) due to their resource constraints. The first challenge arises from the changes in the concept of customer intelligence over the past 20 years on account of the technological revolution in the age of big data. With limited financial resources and analytic capability, many SMEs/SMOs consider technological changes as an obstacle. Additionally, the technological revolution has led to changes in management strategies and organizational structure. The second challenge involves the identification of different types of customer intelligence. Due to the vast nature of this research stream, enterprises seem to lose track of identifying the right type of customer intelligence that fits their need, specifically in the case of SMEs/SMOs. Lastly, the application of specific types of customer intelligence for relevant marketing decisions is not a trivial task. The value of customer intelligence is amplified and leveraged only if enterprises can make use of it for achieving marketing benefits.

These addressed challenges are further validated through the residence in enterprises[1] (la residence en l'enterprise in French) at cultural SMEs/SMOs in Québec. The objective of the residence in enterprises is to validate and enrich the research problems by confronting them with the reality of the business environment. As a result, this real-world experience reveals interesting facts on the status-quo of customer intelligence adoption and affirms the significance of customer intelligence to the cultural sector. The necessity of customer intelligence for marketing benefits stimulates the motivation to consider the cultural sector as the field of research for this study. Building upon the reflections of the literature review and the residence with enterprises, the research objective of the thesis is to develop a customer intelligence model to achieve marketing benefits in the age of big data, particularly for cultural SMEs/SMOs.

Based on the literature review, a conceptual model of customer intelligence for marketing benefits, hereafter called the **CIMB model**, is developed through the lens of service science. The multiple case study strategy is implemented to validate the CIMB model with the cultural organizations in the region of Québec, Canada. Semi-structured interviews are conducted to collect data from the cases of Alpha and Beta. Based on data analysis, the research results reveal the status of adopting customer intelligence for marketing benefits in these cases. Subsequently, the thesis discusses the current, emerging, and future practices of Alpha and Beta. To verify the applicability of the CIMB model, the interactive dashboards are developed by data of Alpha and Beta. Based on the research results, the thesis also recommends a maturity model for adopting customer intelligence for marketing benefits.

Bearing in mind the relatively sparse literature on customer intelligence, the thesis makes significant theoretical contributions by revealing interesting findings. Firstly, the importance and originality of this study are that it develops a customer intelligence model for achieving marketing benefits. A substantial point to ponder is that the CIMB

[1] A 6-credit course offered by UQTR in which students work directly with enterprises to identify managerial problems and envisage solutions.

model classifies different types of customer intelligence along with data sources which is a challenge for most enterprises. The research results demystify customer intelligence with four specific types including product-aware intelligence, customer DNA intelligence, customer experience intelligence, and customer value intelligence. Corresponding data types, data sources, analytic techniques, and marketing benefits for each type of customer intelligence are also identified.

In terms of practical contributions, the thesis sheds light on the complex nature of customer intelligence in the era of big data. Considering such complexity, the CIMB model would assist enterprises to stay on track in reaching strategic goals. The maturity model proposed from the research results can serve as a roadmap for enterprises to avoid losing track of accomplishing marketing benefits from customer intelligence. Therefore, enterprises, particularly cultural SMEs/SMOs, can confide in the proposed model to determine relevant types of customer intelligence along with data sources and analytic techniques that match their capabilities and strategic objectives. Each relevant type of customer intelligence is clarified with specific marketing benefits. This would leverage the value creation from customer intelligence and distinguish the thesis from previous studies.

SYNTHÈSE

L'ère des données massives a suscité un intérêt croissant des entreprises à adopter l'intelligence client pour survivre et prospérer dans une concurrence féroce. L'intelligence client, qui est définie comme des informations et des connaissances acquises par l'analyse commerciale à partir de données générées par les utilisateurs sur des plateformes numériques, devient un moyen précieux pour soutenir les décisions basées sur les données en marketing. La littérature a spécifiquement abordé la supériorité de l'intelligence client dans l'économie actuelle et les opportunités pour les entreprises d'en tirer parti pour des bénéfices marketing. L'application de l'intelligence client offre des solutions gagnant-gagnant pour les entreprises et les clients. D'une part, les entreprises peuvent améliorer leurs performances marketing et financières ; d'autre part, les clients peuvent augmenter leur satisfaction et leur expérience avec les produits/services.

Indépendamment des opportunités prometteuses, l'intelligence client pose également d'énormes défis aux entreprises, en particulier aux petites et moyennes entreprises et organisations (PME/PMO) en raison de leurs contraintes de ressources. Le premier défi découle de l'évolution du concept d'intelligence client au cours des 20 dernières années à cause de la révolution technologique à l'ère des données massives. Avec des ressources financières et une capacité d'analyse limitées, de nombreuses PME/PMO considèrent les changements technologiques comme un obstacle. De plus, la révolution technologique a entraîné des changements dans les stratégies de gestion et la structure organisationnelle. Le deuxième défi consiste à identifier les différents types d'intelligence client. En raison de la nature vaste de ce courant de recherche, les entreprises semblent perdre de vue l'identification du bon type d'intelligence client qui correspond à leurs besoins, en particulier dans le cas des PME/PMO. Enfin, l'application de types spécifiques d'intelligence client pour les décisions marketing pertinentes n'est pas une tâche triviale. La valeur de l'intelligence client n'est amplifiée et exploitée que si les entreprises peuvent l'utiliser pour obtenir des bénéfices marketing.

Ces défis abordés sont ensuite validés par la résidence en entreprise dans des PME/PMO culturelles du Québec. L'objectif de la résidence en entreprise est de valider et d'enrichir les problématiques de recherche en les confrontant à la réalité de l'environnement de l'entreprise. En conséquence, cette expérience du monde réel révèle des faits intéressants sur le statu quo de l'adoption de l'intelligence client et affirme l'importance de l'intelligence client pour le secteur culturel. La nécessité de l'intelligence client pour les bénéfices marketing stimule la motivation à considérer le secteur culturel comme le domaine de recherche de cette étude. S'appuyant sur les réflexions de la revue de la littérature et de la résidence avec les entreprises, l'objectif de recherche de la thèse est de développer un modèle d'intelligence client pour obtenir des bénéfices marketing à l'ère des données massives, en particulier pour les PME/PMO culturelles.

Pour la justification et le renforcement de la motivation de la recherche, une revue de la littérature est menée pour identifier et examiner les articles pertinents liés à l'intelligence client à l'ère des données massives. La revue de la littérature est réalisée en se fondant sur la théorie des ressources (Barney, 1991), la théorie de la connaissance (Grant, 1996), la théorie de la contingence (Lawrence & Lorsch, 1967) et la théorie de la SDL (Service-Dominant Logic) (Vargo & Lusch, 2004). Premièrement, la théorie des ressources prend en charge les données massives et l'analyse des données en tant que ressources et capacités (Barney, 1991). Deuxièmement, la théorie de la connaissance renforce le rôle de l'intelligence client en tant que connaissance (Grant, 1996). Ensuite, la théorie de la contingence examine la congruence entre l'intelligence client et les entreprises. Enfin, la théorie de la SDL (Vargo & Lusch, 2004) ajoute de la valeur à l'application de l'intelligence client pour des bénéfices marketing. En se basant sur la revue de la littérature, la thèse a clarifié et affiné la définition de l'intelligence client pour s'adapter à l'évolution des données massives. Par la suite, la thèse a caractérisé l'intelligence client à travers la valeur, les ressources et les formes d'engagement pour stimuler le processus de co-création de l'intelligence client. Enfin, la thèse aborde les bénéfices marketing à travers les dimensions de la gestion, de la science et de l'ingénierie de la science des services.

Sur la base de la revue de la littérature, un modèle conceptuel d'intelligence client pour les bénéfices marketing, ci-après appelé le modèle **CIMB**, est développé à travers le prisme de la science des services. Dans le modèle proposé, les constructions clés liées aux données client, à l'analyse client, à l'intelligence client et aux bénéfices marketing sont élucidées. La revue de la littérature clarifie également les questions de recherche de la thèse. Ainsi, la première question de recherche porte sur la transformation des données clients en intelligence client à l'ère des données massives compte tenu du contexte des PME/PMO du secteur culturel. La deuxième question de recherche implique l'application de l'intelligence client pour obtenir des bénéfices marketing.

Les questions de recherche ont jeté les bases de la conception de la recherche de la thèse. Par conséquent, la thèse présente la conception de la recherche en rapport avec le paradigme de la recherche, l'épistémologie, les approches, les stratégies, l'échantillon, les techniques de collecte et d'analyse des données. Dans le but d'en savoir plus sur l'intelligence client et ses applications pour les bénéfices marketing, ces questions de recherche ont identifié le paradigme de recherche de la thèse comme étant qualitatif. Sous les fondements philosophiques de la recherche qualitative, cette thèse est basée sur le constructionnisme social, dans lequel la connaissance est construite à travers les interactions entre les personnes dans une société. Par conséquent, cette étude met l'accent sur l'importance du subjectivisme en tant que réalité qui peut être interprétée différemment par les points de vue des constructionnistes. Compte tenu de la nature de la recherche qualitative, l'auteur propose les stratégies de l'étude de cas pour correspondre aux questions de recherche. La stratégie d'études de cas multiples est mise en œuvre pour valider le modèle CIMB auprès des organismes culturels de la région du Québec, Canada. Des entretiens semi-structurés sont menés pour collecter des données à partir des cas Alpha et Beta. La thèse adopte l'analyse thématique pour analyser les données. Les données sont analysées à deux niveaux : analyse intra-cas au sein d'un cas et analyse inter-cas parmi les cas.

Sur la base de l'analyse des données, les résultats de la recherche révèlent l'état de l'adoption de l'intelligence client pour les bénéfices marketing dans ces cas. Bien qu'Alpha et Beta opèrent sur le même marché culturel, ils ne sont pas des concurrents directs, et leurs produits sont bien distincts : spectacles de théâtre pour Alpha alors qu'expositions et locations de salles pour Beta. En fait, il existe une interrelation entre la consommation d'événements culturels d'Alpha et de Beta. Les consommateurs culturels ont tendance à consommer des spectacles de théâtre après l'activité muséale. Comme l'a mentionné le directeur d'Alpha, un nombre important de sources de trafic proviennent des sites Web des musées. De plus, les résultats des entretiens révèlent que ces organisations ont acquis différents types de données clients à partir de transactions, de Google Analytics, de Facebook Insights, de systèmes de point de vente, d'applications, etc. Cependant, transformer les données clients en intelligence client pour créer de la valeur est une tâche difficile. Premièrement, les organisations culturelles trouvent difficile d'extraire des données de différentes sources pour optimiser les décisions basées sur les données. Les gestionnaires culturels estiment qu'ils ne peuvent pas se fier au résultat d'analyse d'une seule source de données. Deuxièmement, les responsables et directeurs d'Alpha et de Beta ont exprimé l'importance d'analyser les données récentes pour soutenir le processus de prise de décision. En effet, les responsables culturels s'appuient sur des techniciens informatiques pour combiner des données provenant de différentes sources. Ce processus prend du temps ; ainsi, les gestionnaires ne sont pas en mesure de travailler directement avec les données et de prendre des décisions sur la propriété « en temps réel » des données. La caractéristique de récence des données est importante pour améliorer la qualité des décisions fondées sur les données. Cela stimule le besoin de tableaux de bord interactifs ou de systèmes d'intelligence client qui permettent aux responsables d'effectuer différentes tâches allant de l'importation, l'exportation, le nettoyage et l'intégration de données à la génération et la visualisation de l'intelligence client pour le processus de prise de décision. Enfin, les responsables et directeurs de ces organisations partageaient une vision commune de l'application de l'intelligence client pour les bénéfices marketing. Alpha s'intéresse aux décisions marketing liées à la segmentation intelligente, à la valeur client, aux partages de voix sur les réseaux sociaux et au tableau de bord interactif. Beta vise à appliquer l'intelligence client pour l'innovation, la performance financière, les décisions contextuelles et les systèmes d'aide à la décision.

Les résultats de la recherche soulignent également la différence entre les cas. Le cas Alpha met en évidence l'importance de la conversion des clients, de l'engagement des clients et de la segmentation à l'aide des services ou des outils d'analyse. En d'autres termes, Alpha se concentre sur l'intelligence de l'expérience client et l'intelligence de l'ADN client. D'un autre côté, Beta reconnaît la diversité et l'importance des « sources de données ». Cependant, les entreprises sont en quelque sorte confus quant à la définition du bon type d'intelligence client. C'est l'un des défis importants auxquels la plupart des PME/PMO sont confrontées. Un signal positif est que Beta montre son intérêt pour l'apprentissage de la segmentation de la clientèle et sa volonté d'investir dans les technologies de l'information pour intégrer des données provenant de diverses sources.

Sur la base des résultats de la recherche, la thèse discute des pratiques actuelles, émergentes et futures d'Alpha et Beta. Les trois étapes de la pratique peuvent servir de feuille de route pour l'adoption de l'intelligence client à des bénéfices marketing. La pratique actuelle est révélée sur la base de l'analyse des données. La pratique émergente propose les actions du futur proche qu'Alpha et Beta peuvent prendre en considération, tandis que la pratique future se concentre sur les stratégies à long terme. Pour vérifier l'applicabilité du modèle CIMB, les tableaux de bord interactifs sont développés par les données d'Alpha et Beta. Sur la base des résultats de la recherche, la thèse recommande également un modèle de maturité pour adopter l'intelligence client à des bénéfices marketing. Le modèle de maturité s'appuie sur l'outil de diagnostic pour identifier le statu quo des entreprises et proposer des lignes directrices pertinentes pour obtenir des bénéfices marketing grâce à l'intelligence client. Sur la base de l'outil de diagnostic, le modèle de maturité classe trois niveaux comme suit : En développement (1-4), Intermédiaire (5-8) et Mature (9-10). Des directives spécifiques sont décrites à chaque niveau.

Compte tenu de la littérature relativement rare sur l'intelligence client, la thèse apporte des contributions théoriques importantes en révélant des résultats intéressants. Premièrement, l'importance et l'originalité de cette étude sont qu'elle développe un modèle d'intelligence client pour obtenir des bénéfices marketing. Un point important à considérer est que le modèle CIMB classe différents types d'informations sur les clients ainsi que des sources de données, ce qui est un défi pour la plupart des entreprises. Les résultats de la recherche démystifient l'intelligence client avec quatre types spécifiques, notamment l'intelligence sensible au produit, l'intelligence ADN client, l'intelligence de l'expérience client et l'intelligence de la valeur client. Les types de données, les sources de données, les techniques analytiques et les bénéfices marketing correspondants pour chaque type d'intelligence client sont également identifiés.

En termes d'apports pratiques, la thèse met en lumière la nature complexe de l'intelligence client à l'ère des données massives. Compte tenu d'une telle complexité, le modèle CIMB aiderait les entreprises à rester sur la bonne voie pour atteindre leurs objectifs stratégiques. Le modèle de maturité proposé à partir des résultats de la recherche peut servir de feuille de route aux entreprises pour éviter de perdre de vue les bénéfices marketing de l'intelligence client. Par conséquent, les entreprises, en particulier les PME/PMO culturelles, peuvent se fier au modèle proposé pour déterminer les types pertinents d'intelligence client ainsi que les sources de données et les techniques d'analyse qui correspondent à leurs capacités et objectifs stratégiques. Chaque type pertinent d'intelligence client est clarifié avec des bénéfices marketing spécifiques. Cela tirerait parti de la création de valeur de l'intelligence client et distinguerait la thèse des études précédentes.

ABSTRACT

Even though customer intelligence is catching the attention of academics and practitioners due to promising opportunities, enterprises, particularly small and medium-sized enterprises and organizations (SMEs/SMOs), find it challenging to adopt customer intelligence for marketing benefits. Customer intelligence, which is defined as understanding or insights resulting from the application of analytic techniques, plays a significant role in the survival and prosperity of enterprises in the knowledge-based economy. In this light, the thesis develops a model of customer intelligence for marketing benefits, hereafter called the CIMB model. The proposed model aims at supporting enterprises to identify the right customer data for the right customer intelligence corresponding with the right marketing benefits. Accordingly, four types of customer intelligence are clarified, including product-aware intelligence, customer DNA intelligence, customer experience intelligence, and customer value intelligence. The applications of customer intelligence are also elucidated with relevant marketing benefits to maximize value creation. The CIMB model is validated by two cultural organizations in the region of Québec, Canada. The research results reveal interesting facts about the adoption of customer intelligence in these cultural organizations. The thesis also discusses emerging and future practices. To illustrate the applicability of the CIMB model, interactive dashboards are developed from the data of these organizations. The importance and originality of this study are that it responds to changes in customer intelligence in the age of massive data and covers multifaced aspects of marketing benefits.

Keywords: customer intelligence, marketing benefits, big data, cultural sector, SMEs/SMOs

RÉSUMÉS

Même si l'intelligence client attire l'attention des chercheurs et des praticiens en raison d'opportunités prometteuses, les entreprises, en particulier les petites et moyennes entreprises et organisations (PME/PMO), trouvent difficile d'adopter l'intelligence client pour des bénéfices marketing. L'intelligence client, définie comme la compréhension ou les connaissances résultant de l'application de techniques analytiques, joue un rôle important dans la survie et la prospérité des entreprises de l'économie du savoir. À cet égard, la thèse développe un modèle d'intelligence client pour les bénéfices marketing, ci-après appelé le modèle CIMB. Le modèle proposé vise à aider les entreprises à identifier les bonnes données client pour la bonne intelligence client correspondant aux bons bénéfices marketing. En conséquence, quatre types d'intelligence client sont clarifiés, notamment l'intelligence sensible aux produits, l'intelligence de l'ADN client, l'intelligence de l'expérience client et l'intelligence de la valeur client. Les applications de l'intelligence client sont également expliquées avec des bénéfices marketing pertinents pour maximiser la création de valeur. Le modèle CIMB est validé par deux organismes culturels de la région de Québec, Canada. Les résultats de la recherche révèlent des faits intéressants sur l'adoption de l'intelligence client dans ces organisations culturelles. La thèse aborde également les pratiques émergentes et futures. Pour illustrer l'applicabilité du modèle CIMB, des tableaux de bord interactifs sont développés à partir des données de ces organisations. L'importance et l'originalité de cette étude résident dans le fait qu'elle répond aux évolutions de l'intelligence client à l'ère des données massives et couvre des aspects multiformes des bénéfices marketing.

Mots-clés : intelligence client, bénéfices marketing, données massives, secteur culturel, PME/PMO

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AI	Artificial intelligence
CEO	Chief executive officer
CI	Customer intelligence
CIMB	Customer intelligence model for marketing benefits
DST-CO	Decision supporting tool for cultural organizations
KPI	Key performance indicators
GDP	Gross Domestic Product
IT	Information technology
RQ	Research question
SMEs	Small and medium-sized enterprises
SMOs	Small and medium-sized organizations
STP	Segmentation, targeting, and positioning
OECD	Organization for economic co-operation and development
PME	Petites et moyennes entreprises
PMO	Petites et moyennes organisations
POS	Point of sale
UNESCO	The United Nations Educational, Scientific and Cultural Organization

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INTRODUCTION

In the age of big data, customer intelligence plays a significant role in the survival and prosperity of enterprises (Bender et al., 2020; Colbert & Dantas, 2019; Ruiz et al., 2017). Customers create a significant amount of data through interactions on digital platforms, which has become a valuable source of knowledge to improve marketing decisions (Anshari et al., 2019; Yan et al., 2020; Zerbino et al., 2018). In this vein, enterprises make tremendous efforts to transform customer data into customer intelligence that is defined as understandings or insights resulting from the application of analytic techniques. Customer intelligence has been proven as a stimulant to turn enterprises into top performers in the marketplace with at least a 6% gain on profits (McAfee et al., 2012).

Great potentials of customer intelligence have fueled attention towards the competitive advantages of enterprises, particularly SMEs/SMOs (Holmlund et al., 2020; Yan et al., 2020). However, most enterprises are not clear on what customer intelligence is as it lies at the junction of big data and customer insights (Davenport & Spanyi, 2019; Tabrizi et al., 2019). The matrix of customer intelligence application has confused executives with identifying relevant types of customer intelligence along with data types and sources. The literature revealed that enterprises are obsessed to take advantage of customer intelligence; nevertheless, they lose track due to the vast nature of this research domain (Jagadish, 2015; Lau et al., 2016). In fact, the majority of enterprises tend to overemphasize the importance of technological changes from the revolution of big data while lacking the mindset of restructuring the organizational and management viewpoints to create value towards marketing benefits (Anshari et al., 2019; Tabrizi et al., 2019; Yohn, 2018).

The motivation to apply customer intelligence for marketing benefits is strengthened through the residence in enterprises with SMEs/SMOs in the cultural sector. Limited constraints in analytic skills and finance do not impede these cultural SMEs/SMOs from adopting customer intelligence. In fact, these cultural organizations give a positive signal in applying customer intelligence for marketing benefits due to the diverse data and a strong vision. Considering the importance of customer intelligence for cultural SMEs/SMOs based on the literature review, the residence in enterprises, and interviews with cultural organizations in the region Québec, Canada, the thesis focuses on the cultural sector as the field study. Building from these reflections, the research purpose is to demystify the concept of customer intelligence and its application for marketing benefits, particularly in the context of cultural SMEs/SMOs. To explore the research purpose, the structure of this thesis is developed as follows.

Chapter 1 aims at exploring the managerial problems in the context of customer intelligence in the age of big data. This chapter also presents the validation of the managerial problems through the residence in enterprises at SMEs/SMOs in the cultural sector. Findings from the residence combined with the analysis of literature related to customer intelligence have reinforced the research motivation of the thesis and the selection of the cultural sector as the field of study.

Chapter 2 focuses on the literature review to further investigate the research motivations in Chapter 1. The literature review lays its profound foundation on the theories relevant to customer intelligence. In this chapter, the process of identifying and reviewing the selected articles is described to ensure the validity of the literature review. Afterward, the chapter presents the analysis of findings from the reviewed articles. Chapter 2 ends with a discussion of the research gaps based on the literature review.

Chapter 3 focuses on proposing a conceptual model of customer intelligence for marketing benefits and clarifying the research questions. Literature stimulates the need to clarify specific types of customer intelligence. Consequently, the objective of this chapter is to propose a conceptual model and to define the research questions with relevance to the particular types of customer intelligence and their applications to achieve marketing benefits. The chapter ends with the classification of the proposed research questions which sets the foundation for the research design.

Chapter 4 presents the research design regarding the research paradigm, epistemology, approaches, strategies, sample, data collection, and analysis techniques. To ensure the reliability, generalizability, and validity of the research results, challenges related to these criteria are also discussed. The chapter also justifies the attempts to improve the research quality with respect to the reliability, generalizability, and validity of the findings.

Chapter 5 presents the research results and discussions. The objective of this chapter is to analyze interview data in reflection to the conceptual model of customer intelligence for marketing benefits. Based on the analysis of the multiple case study, Chapter 5 discusses the current, emerging, and future practices of Alpha and Beta. The discussion section also verifies the applicability of the proposed model in Chapter 3 by the demonstration of the interactive dashboards developed for Alpha and Beta. Chapter 5 ends with the recommendation on maturity levels of adopting customer intelligence based on the research results.

Chapter 6 justifies the research theme of the thesis through the discussions on theoretical and practical contributions. Furthermore, the chapter discusses the future direction, research limitations, and research ethics of the thesis. The last section of the chapter concludes with the originality and implications of this study in responding to changes in customer intelligence in the age of big data and leveraging its value toward marketing benefits.

CHAPTER 1
MANAGERIAL PROBLEMS

Chapter 1 aims at exploring the managerial problems in the context of customer intelligence in the age of big data. This chapter also presents the validation of the managerial problems through the residence in enterprises at SMEs/SMOs in the cultural sector. Findings from the residence combined with the analysis of literature related to customer intelligence have reinforced the research motivation of the thesis and the selection of the cultural sector as the field of study.

1.1 RESEARCH CONTEXT

The research context highlights the emergence of big data analytics and the dominance of services and service-based products. These trends have put enterprises under pressure for competition to survive and thrive in the age of big data. In this regard, customer intelligence has emerged as a means to help enterprises achieve marketing benefits.

1.1.1 The emergence of big data and analytics

This section highlights the importance of big data and analytics which are considered a source of competitive advantages for enterprises.

The advancement of information technology (IT) has led to the proliferation of social media, websites, mobile devices, forums, and blogs where users can interact with enterprises and other customers (Davenport & Dyché, 2013; Mikalef, Pappas, et al., 2020). These interactions have created a significant amount of data, which is called big data.

Big data is defined as datasets, whose size is beyond the ability of traditional software tools, that is generated from mobile phones, network servers, social network, and Internet-of-things (Gandomi & Haider, 2015; Hofacker et al., 2016b). New abilities and tools for big data analytics have stimulated decision-makers to shift their focus to data as the "oil of the new economy" (Dam et al., 2021b; Huang & Rust, 2021). In this light, big data have become a key resource for enterprises to create value and gain competitive advantages (Amado et al., 2018; Wamba et al., 2017). Big data can help enterprises in all sectors to make significant advances in customer relationships, product development, and innovation to increase profitability (Lies, 2019; Shim & Taylor, 2019). The adoption of big data undeniably helps managers gain a deeper understanding of their businesses to measure their business performance as well as to improve the decision-making process (Lau et al., 2016; Xu et al., 2016).

Indeed, businesses utilize data through the process of recording and monitoring transactions (Janssen et al., 2017; Rao et al., 2019). Big data analytics has enabled the analytical value of data, which has been ground in recent years and is reflected by the growing interest in business analytics. In general, the term "big data analytics" can be considered the utilization of advanced business analytics techniques for the analysis of big data sets (Amado et al., 2018; Verma, 2017). Business analytics can be classified as descriptive, predictive, and prescriptive analytics: i) *Descriptive analytics* aims at exploring historical data and transforms them into insights using different techniques such as business reporting, descriptive statistics, and visualization (Liang & Liu, 2018; Pappas et al., 2018), ii) *Predictive analytics* deals with the forecast of future possibilities to make information more actionable (Lau et al., 2016; McAfee et al., 2012), and iii) *Prescriptive analytics* determines the most optimal solutions for specific practical scenarios through simulation and optimization (Chen et al., 2012; Holmlund et al., 2020).

1.1.2 The dominance of services and service-based products

The age of big data has acknowledged the dominance of services and service-based products in the modern economy (Baines et al., 2017; Vargo & Lusch, 2017). Consequently, this section highlights such dominance along with the characteristics of services and service-based products.

The era of big data has witnessed the dominance of services and service-based products (Im & Qu, 2017; Mikalef, Krogstie, et al., 2020). A point to ponder is that a service is no longer considered an extra offering or an output of products (Hollebeek et al., 2019; Opresnik & Taisch, 2015). Service-oriented enterprises perceive a service as a solution to deliver value for customers instead of products (Lenka et al., 2017; Zhang & Banerji, 2017). Statistics show that the service sector makes a significant contribution to the national Gross Domestic Product (GDP), particularly in developed countries with over two-thirds (Szirmai & Verspagen, 2015). Nowadays, products cannot survive without the companion of services. In fact, the revolution of big data has reshaped the definition of services as well as business strategies (Huang & Rust, 2018). Many manufacturing enterprises have to adjust their business strategies with the service orientation to adapt to changes in the modern economy (Baines et al., 2017; Vargo & Lusch, 2017).

Nowadays, services and service-based products are developed, personalized, and recommended to users based on their preferences and contexts (Beverungen et al., 2019; Spohrer & Demirkan, 2015). Service providers maintain a continuous connection with customers; therefore, customer data are constantly updated for service development and innovation (Samuel, 2015; Siggelkow & Terwiesch, 2019). Services and service-based products are offered in the sense that they are dynamic, context-aware, and interconnected to provide personalized solutions for customers (Chianese & Piccialli, 2016; Lim & Maglio, 2018). Enterprises, including small and medium-sized enterprises and organizations (SMEs/SMOs), often reshape their business strategies with service orientation to gain sustainable competitive advantages in the age of big data (Opresnik & Taisch, 2015; Zhang & Banerji, 2017).

1.1.3 Customer intelligence for marketing benefits

Derived from big data, customer intelligence has shown great potential for marketing benefits. This section introduces the concept of customer intelligence with an update on data sources in the age of big data. Potentials of customer intelligence for marketing benefits are then presented.

The big data era has opened up incredible opportunities for enterprises to promote digital transformation via marketing benefits related to customer intelligence from big data (Sivarajah et al., 2017; Yan et al., 2020). Being described as extremely large data sets in volume, velocity, variety, and veracity, big data are considered a great source for insights into customers, hereafter called customer intelligence (Janssen et al., 2017; Lau et al., 2016). More specifically, customer intelligence can be perceived as knowledge or insights on customers that can be acquired from data mining techniques and then apply them to achieve marketing benefits (Efrat et al., 2017; Huster, 2005). From the business point of view, customer intelligence enables enterprises to develop services and service-based products, to identify potential customers, and to customize marketing strategies (Anshari et al., 2019; Dam et al., 2019).

Nowadays, customer intelligence relies on big data and analytic techniques to gather information on customers in a more efficient way (Chen et al., 2012; Davenport & Spanyi, 2019). Therefore, customer intelligence can be acquired from web intelligence by mining Internet Protocol searches, cookies, and server logs. Through web pages and e-commerce sites, data on potential customers can be acquired through their reviews or feedback to uncover customers' needs (Chen et al., 2018; Trischler et al., 2017). Other types of customer data from web intelligence are clickstream data logs that record customers' activities on visit frequency, viewed items, and visit time on a website (Fan et al., 2015; Park et al., 2012). Likewise, customer intelligence is strongly reflected in the form of social intelligence through sentiment analysis and opinion mining on numerous customers' comments on social media and e-commerce sites (Lau et al., 2014; Li & Li, 2013). Social intelligence extracted from user-contributed data on social media can support enterprises with innovating services/products, implementing marketing strategies, managing customer relationships, and improving service quality (Stone et al., 2017; Zerbino et al., 2018). The real-time property of social intelligence along with its subjectivity in a specific context is significantly believed to be more trustworthy, updated, and reliable compared to traditional sources of information (Archak et al., 2011; Lau et al., 2014). Consequently, customer intelligence from social media as a source of big data is strongly believed to support enterprises to gain a competitive advantage by offering services/products that satisfy customers' needs (Liang & Liu, 2018; Xie et al., 2016).

The application of customer intelligence has been proven as a stimulant to turn enterprises into top performers in the marketplace with at least a 6% gain on profits (McAfee et al., 2012). Accordingly, customer intelligence is believed to enterprises in developing products/services, understanding customer behaviors, and improving marketing strategies (Anshari et al., 2019; Yan et al., 2020; Zerbino et al., 2018). Customer intelligence is applied to different marketing aspects associated with the decision-making process, including predicting customers' needs, segmentation, service innovation, promotional strategies, pricing strategies, and customer lifetime value estimation (France & Ghose, 2018; Sivarajah et al., 2017). With the support of customer intelligence, enterprises can provide tailored products/services (for example, recommender systems) and optimize marketing decisions (Dam et al., 2022; Tasic et al., 2020). Enterprises, therefore, can improve their marketing and financial performance whereas customers can increase their satisfaction and experience with products/services (Holmlund et al., 2020; Tabrizi et al., 2019). As an illustration, the application of customer intelligence in recommender systems promotes the optimization of customer experience in finding relevant products/services and engaging with enterprises (Schafer et al., 2007; Zhang & Min, 2016). Taking advantage of customer intelligence as recommendation services, Netflix and Amazon have achieved a significant financial boost (Siggelkow & Terwiesch, 2019; Xie et al., 2016). Another illustration of customer intelligence for marketing benefits is the development of chatbots for online conversations via text or text-to-speech (Chung et al., 2018). Chatbots can deal with many customers at the same time. Therefore, customers can get faster responses from conversational agents while enterprises can reduce service costs (Ranoliya et al., 2017).

1.2 MANAGERIAL PROBLEMS

This section clarifies the managerial problems with relevance to big data, the application of customer intelligence for marketing benefits, and restrictions of SMEs/SMOs (Table 1.1). For each managerial problem, specific challenges are discussed in detail. As big data, in general, and customer intelligence, in particular, belong to multidisciplinary research, each challenge is also classified through the lens of service science, including the dimensions of science, management, and engineering (Maglio & Spohrer, 2013; Spohrer et al., 2007). The science dimension focuses on the organizational viewpoint whereas the management dimension covers the strategic viewpoint. The engineering dimension touches upon the technological viewpoint.

Table 1.1
Summary of challenges related to managerial problems

Challenges	**Managerial Problems**	**Service Science**	**References**
Big data capture	Big data	Engineering	Hu et al. (2014); Lau et al. (2016); LaValle et al. (2011); Mikalef, Pappas, et al. (2020); Weinberg et al. (2013).
Big data integration	Big data	Engineering	Anshari et al. (2019); Gandomi and Haider (2015); Holmlund et al. (2020); Rao et al. (2019); Shim and Taylor (2019); Weinberg et al. (2013).
Big data analytics	Big data	Engineering	Chen et al. (2012); Erevelles et al. (2016); Hu et al. (2014); LaValle et al. (2011); Mikalef, Pappas, et al. (2020); Sahatiya (2018).
Big data quality	Big data	Engineering	Chen et al. (2012); Erevelles et al. (2016); Hu et al. (2014); LaValle et al. (2011); Mikalef, Pappas, et al. (2020); Sahatiya (2018).
Overemphasis on technological changes	Application of customer intelligence	Engineering	Anshari et al. (2019); Del Vecchio et al. (2018); Taghizadeh et al. (2018); Yan et al. (2020); Yohn (2018).
Lacks analytic skills of managers to support marketing decisions	Application of customer intelligence	Management	Bianchini and Michalkova (2019); Davenport (2006); Fan et al. (2015); Gandomi and Haider (2015); Pappas et al. (2018); Wamba et al. (2017).
Identification of relevant customer intelligence for marketing benefits.	Application of customer intelligence	Management	Chen et al. (2021); Dam et al. (2021a); France and Ghose (2019); Huang and Rust (2021); Lies (2019).
Unclear vision and leadership	Application of customer intelligence	Science	Tabrizi et al. (2019); Ramaswamy and Ozcan (2019); McAfee et al. (2012); Roberts et al. (2016).

Challenges	**Managerial Problems**	**Service Science**	**References**
Restructure of organizational structure	Application of customer intelligence	Science	Tabrizi et al. (2019); Ramaswamy and Ozcan (2019); McAfee et al. (2012); Roberts et al. (2016).
Lack of data	Big data and SMEs/SMOs	Engineering	Bianchini and Michalkova (2019); Cacciolatti and Fearne (2013); Coleman et al. (2016); Saura et al. (2021); Willetts et al. (2020).
Limit of analytic skills	SMEs/SMOs	Science	Bianchini and Michalkova (2019); Cacciolatti and Fearne (2013); Coleman et al. (2016); Saura et al. (2021); Willetts et al. (2020).
Lack of data specialists	SMEs/SMOs	Science	Bianchini and Michalkova (2019); Cacciolatti and Fearne (2013); Coleman et al. (2016); Saura et al. (2021); Willetts et al. (2020).
Financial barriers	SMEs/SMOs	Science	Bianchini and Michalkova (2019); Cacciolatti and Fearne (2013); Coleman et al. (2016); Saura et al. (2021); Willetts et al. (2020).
Lack of SMEs/SMOs-tailored solutions	SMEs/SMOs	Engineering	Bianchini and Michalkova (2019); Cacciolatti and Fearne (2013); Coleman et al. (2016); Saura et al. (2021); Willetts et al. (2020).
Lack of business cases	SMEs/SMOs	Management	Bianchini and Michalkova (2019); Cacciolatti and Fearne (2013); Coleman et al. (2016); Saura et al. (2021); Willetts et al. (2020).

Source: Dam (2021)

1.2.1 Challenges from big data

To take advantage of big data, enterprises have to deal with challenges in big data capture, integration, analytics, and quality (Baesens et al., 2016; Chen et al., 2012; Holmlund et al., 2020; Mikalef, Pappas, et al., 2020). Generally speaking, challenges from big data focus on the engineering dimension of service science.

Several enterprises have successfully managed their business thanks to the ability to collect, analyze, and make decisions based on big data (Janssen et al., 2017; Van Auken, 2015). However, it is not easy for them to capture big data in order to transform information into awareness and actions (Sivarajah et al., 2017). The challenge in capturing relevant customer data comes from the diversity of data sources (Baesens et al., 2016; Moges et al., 2013). The study of Baesens et al. (2016) points out that accessing big data sources to ensure data quality is a real mantra when using big data. It is not easy to identify relevant sources of customer data due to the problems of data overload (Hofacker et al., 2016a; Kumar et al., 2013) and data quality (Baesens et al., 2016; Moges et al., 2013).

Although the amount of information is big and can be found everywhere (Kumar et al., 2013), 80% of enterprises lack customer data, especially the ability to integrate data for sales or customer practices (Leeflang et al., 2014). This indicates the challenge of combining different data streams to find out the interrelationships of big data (Baesens et al., 2016; Van Auken, 2015). The value of data will be significantly leveraged when combining and linking several sources of data (Wamba et al., 2017; Weinberg et al., 2013). Integrating various sources of big data for customer intelligence enhances the accuracy of customer-data-driven decisions. However, the integration of different sources of customer data also involves challenges regarding data privacy and security (Weinberg et al., 2013; Yan et al., 2020). Optimizing customer data value while considering ethical issues associated with customers such as privacy and anonymity seems to be a great challenge for enterprises (George et al., 2014; Janssen et al., 2017; McAfee et al., 2012).

Customer intelligence relies on applying analytics to gain intelligence from big data and then apply it to the decision-making process (Davenport et al., 2020; Opresnik & Taisch, 2015). The process of data transformation requires strenuous efforts from data integration to data analytics (Chevallier et al., 2016; Tian, 2017). Data analytic techniques including, descriptive, predictive, and prescriptive, – which are applied to analyze and interpret data – explain insights underlying the meaningless customer data (Davenport & Dyché, 2013; LaValle et al., 2011). However, challenges arise from how to apply algorithms for analytics, especially with predictive and prescriptive analytics. These analytics rely on quantitative techniques and algorithms such as statistic modeling, regression, neural network algorithms, and machine learning techniques to transform customer data into customer intelligence (Gandomi & Haider, 2015; García et al., 2017). Therefore, it is a challenging task for enterprises to work with data through analytics for customer intelligence (Baesens et al., 2016; Janssen et al., 2017; Moges et al., 2013).

As a multidimensional concept, data quality includes a variety of data properties such as accuracy, completeness, latency, security, interpretability, and data traceability (Moges et al., 2013). Therefore, the nature of data quality is assessed differently depending on problem domains with an acceptable margin of error (Wamba et al., 2017; Weinberg et al., 2013). In addition, data overload is considered a significant factor that influences the quality of acquired data (Anshari et al., 2019; Yan et al., 2020; Zerbino et al., 2018). Data is overloaded because the same data are recorded in various databases, and the existing data are not updated and well organized (Hofacker et al., 2016a). As the inconsistency, duplication, and diversity of many data sources cause data overload, it requires significant effort to clean and get rid of overlapped data (France & Ghose, 2018; Sivarajah et al., 2017).

1.2.2 Challenges from the application of customer intelligence for marketing benefits

To apply customer intelligence for marketing benefits, enterprises have to overcome the challenges related to the overemphasis on technological changes, identification of relevant customer intelligence for marketing benefits, the lack of analytic skills of managers, unclear vision and leadership, and adaptation of organizational structure (Lies, 2019; Sutcliff et al., 2019; Yohn, 2018; Zerbino et al., 2018). These challenges deal with different dimensions of service science.

The majority of enterprises overemphasize the importance of technological changes and lack the mindset of restructuring the organizational and strategic viewpoints to better offer service to customers (Yohn, 2018). Technological changes within enterprises might aggravate flaws in strategy and organization (Sutcliff et al., 2019; Tabrizi et al., 2019). The most significant thing in the revolution of customer big data is not a technological problem (Newman, 2018). It is about how to apply big data to create value for enterprises and customers. The value of customer intelligence from big data is how enterprises understand customers, design, and deliver optimal marketing solutions for customers (McGrath & McManus, 2020; Newman, 2018). To put it in other words, enterprises make use of customer intelligence in adapting their business strategies and organizational structure to offer marketing solutions that can satisfy customers' preferences (Lafrenière, 2020; McGrath & McManus, 2020).

Another challenge involves the identification of different types of customer intelligence (Anshari et al., 2019; Dam et al., 2021a). Due to the vast nature of this research stream, enterprises seem to lose track in identifying the right type of customer intelligence that fits their need, especially in the case of small and medium-sized enterprises (Chen et al., 2021; Huang & Rust, 2021). The application of specific types of customer intelligence for relevant marketing decisions is not a trivial task (Alves et al., 2016; Davenport et al., 2020). The value of customer intelligence is amplified and leveraged only if enterprises can make use of it for marketing decisions (Erevelles et al., 2016; Wedel & Kannan, 2016).

The ability of managers to understand data and apply customer intelligence from data analysis plays a significant role in leveraging the value of customer intelligence (Khan & Vorley, 2017; Mikalef et al., 2019). Analytics skills along with intuition encourage managers to take advantage of customer intelligence to support marketing decisions to respond to dynamic changes from customers and markets (Wamba et al., 2017; Wedel & Kannan, 2016).

To create value from customer intelligence, it is necessary to have a clear vision and leadership with specific goals concerning product and service offerings (Tabrizi et al., 2019). Accordingly, managers and directors need to have a customer-oriented mindset that prioritizes the beneficial offerings for customers (Ramaswamy, 2009). In addition, managers should be able to sense opportunities for potential markets (McAfee et al., 2012; Roberts et al., 2016).

The success of transforming customer intelligence depends on many factors related to the organizational structure including organizational culture, staff engagement, communication, and policy. It is important to build an organizational culture supporting data-driven decisions for marketing across all departments of an enterprise (Leeflang et al., 2014). Many enterprises find it challenging to build an organizational culture to encourage staff engagement (Zerbino et al., 2018; J. Z. Zhang et al., 2018). Many problems arise from communications between employees and managers as well as the lack of suitable incentive policies for employees (Burrell, 2018; Yohn, 2018).

1.2.3 Challenges related to SMEs/SMOs

Concerning SMEs/SMOs, the application of customer intelligence brings a wide range of opportunities for SMEs for marketing benefits (Anshari et al., 2019; Rao et al., 2018). However, the adoption of customer intelligence in SMEs is still limited. Various factors leading to the poor adoption of customer intelligence in SMEs/SMOs are presented as follows (Bianchini & Michalkova, 2019; Lu et al., 2020; Saura et al., 2021).

SMEs/SMOs face important challenges in accessing and analyzing relevant data (Castagna et al., 2020; Lu et al., 2020). It is noted that SMEs/SMOs do not often collect and store data in the right format or a sufficient manner (Saura et al., 2021; Willetts et al., 2020). Therefore, when it comes to analyzing data, these SMEs/SMOs might not have enough data to perform business analytics (Willetts et al., 2020).

Limited analytics skills by management and employees may lead to important challenges related to the adoption of recent digital technologies (Bianchini & Michalkova, 2019; Saura et al., 2021). Managers might be aware of business situations; however, they are not able to identify relevant analytic techniques to support specific marketing decisions. They face the challenge of pulling the right data corresponding with business analytics to facilitate the decision-making process (Cacciolatti & Fearne, 2013; O'Connor & Kelly, 2017).

It is quite difficult for SMEs/SMOs to identify, attract, and retain the data specialists needed to deploy effective data analytics (Coleman et al., 2016). Data specialists tend to work for large companies; therefore, it is challenging for SMEs/SMOs to employ them (Saura et al., 2021; Willetts et al., 2020). This influences long-term strategies, which stimulate the adoption of customer intelligence (Lu et al., 2020).

Lack of financing options and burdensome regulatory requirements often represent additional barriers for SMEs/SMOs (Coleman et al., 2016; Willetts et al., 2020). To adopt customer intelligence, SMEs/SMOs need to invest physical, human, and organizational capitals in building data infrastructure supporting big data analytics such as intranets, data mining tools, cloud-based platforms, automatic identification, and data capture technologies (Baesens et al., 2016; Coleman et al., 2016). This is a great challenge for resource-constrained SMEs/SMOs (Verma, 2017; Willetts et al., 2020).

Many of the currently available analytics products do not necessarily take the specific needs of SMEs/SMOs into account (Coleman et al., 2016; Hofacker et al., 2016b). The solutions of big data acquisition, storage, analysis, and transfer often aim for large enterprises with strong financial capability (Mikalef, Pappas, et al., 2020; Xu et al., 2016). SMEs/SMOs may find it challenging to find affordable products or services that match their needs and help them take advantage of big data (Coleman et al., 2016; Fan et al., 2015).

SMEs/SMOs need exemplary case studies and success stories to reinforce their motivation and set trends in big data adoption. It may be easy for SMEs/SMOs to get lost in adopting big data due to the vast nature of this domain. Consequently, it is a good idea to have some successful business cases to guide SMEs/SMOs in the early stage of adopting big data.

1.3 VALIDATION OF MANAGERIAL PROBLEMS BY THE RESIDENCE IN ENTERPRISES

The previous part of the thesis discusses in detail various problems relevant to customer intelligence in the age of big data. With an aim to validate these managerial problems in the real business context, the residence in enterprises was conducted. The objective of the residence in enterprises is to validate and enrich the research problems by confronting them with the reality of the business environment. In this case, the residence in enterprises aims at examining how enterprises adopt customer intelligence to achieve marketing benefits.

1.3.1 Phases of the residence in enterprises

The residence in enterprises consists of two phases. At first, the residence was conducted with Vietnamese SMEs in the export sector to verify challenges related to big data and analytics. Export enterprises can be an interesting case to see the significance of customer intelligence to achieve marketing benefits in internationalization. The second phase of the residence in enterprises continues the validation process with SMEs/SMOs in Canada. The following part will further present the two phases of the residence in enterprises.

1.3.1.1 Residence with export enterprises in Vietnam

This subsection presents the profiles of exports enterprises and motivations for investigating the export sector in Vietnam. The residence with export enterprises reveals data supporting decisions in internationalization and challenges in adopting customer intelligence.

The residence in enterprises was conducted at Hoa Tho Textile Garment Joint Stock Corporation and Halong Canned Food Joint Stock Corporation in the period of 4 months. The detailed profiles of the two enterprises are provided in Table 1.2. The exporting sector in Vietnam was chosen due to the author's strong network with local enterprises. Furthermore, managers and directors at these enterprises are also interested in adopting big data analytics in general and customer intelligence in particular. In addition, the export sector of Vietnam shows great potential for economic growth as Vietnamese exports, especially in the domains of textiles, food, wearing apparel, and tobacco, are believed to increase by 4.2% by 2030 (Bank, 2018).

Table 1.2
Profiles of export enterprises in Vietnam

Period	Enterprises	Enterprise profiles
02-03/2019	Hoa Tho Textile Garment Joint Stock Corporation	**Domain:** Textiles and garment **Main products:** Jacket, Shirt, T-shirt, Polo-shirt, pants, fabric, etc. **Primary markets:** US, EU, Japan.
03-05/2019	Halong Canned Food Joint Stock Corporation.	**Domain:** Food processing **Main products:** Canned tuna, sardine, and mackerel. **Primary markets:** Asia.

Source: Dam (2020)

Hoa Tho and Halong Corporation make decisions based on data from different sources acquired from the government, trade agreements, agents, or trade associations. Data analytics or the interpretation of raw data is hardly involved in the process of generating "customer intelligence". To be specific, directors at Hoa Tho Corporation make decisions mostly based on trade agreements. For example, they will rely on The Free Trade Agreement or Trans-Pacific Partnership Agreement to come up with export strategies. Other sources of data that they may collect come from trade fairs, agents, Vietnam Textile and Apparel Association, Commercial Counselor, and Google searches. Similarly, Ha Long Corporation makes decisions in internationalization based on trade agreements with the Vietnam government to take advantage of tax support. Ha Long Corporation also collects data from the Vietnam Association of Seafood Exporters and Producers (VASEP), agents, trade fairs, and the Internet.

It is significant to note that most Vietnamese export enterprises do not actively search for customers. Instead, business customers from Europe and America often come to these export enterprises with detailed requests for products. This status-quo brings up two major challenges for the export sector in Vietnam. The first challenge involves the increasing amount of export products; however, brand names of Vietnamese export enterprises cannot be found in foreign markets. In fact, most Vietnamese enterprises just export processed materials to foreign enterprises. Therefore, the economic value is not high; particularly, Vietnamese enterprises cannot build their brands in foreign markets. The second challenge results from the passive capability of acquiring, storing, and analyzing data for data-driven decisions in internationalization. Vietnamese enterprises rely on foreign partners to find them; consequently, they find it challenging to look for and penetrate potential markets. The status-quo of the export sector in Vietnam indicates the unreadiness of the adoption of customer intelligence in the age of big data. Therefore, it might not be a suitable choice to choose the export sector of Vietnam as the field of study at this time.

1.3.1.2 Residence with cultural organizations in Canada

After the first phase, the process of validating the managerial problems continues with SMEs/SMO in Canada. The residence in enterprises was carried out at two cultural SMEs/SMOs in the region of Québec, Canada. This part presents the profiles of cultural organizations and the residence motivation.

Residence with Culture Mauricie and Diffusion Momentum happened due to the research project which supports the local cultural sector. Table 1.3 summarizes the period of the residence and profile descriptions of the two organizations in the cultural sector of Québec, Canada. In attempting to promote regional artistic and cultural growth, Culture Mauricie supports the development of arts and culture in different cultural domains such as visual arts, performing arts, literature, media arts, museums, and heritage[2]. On the other hand, Diffusion Momentum is the only professional cultural show broadcaster in Victoriaville and also the owner of Victoriaville's cultural space, Carré 150[3]. Diffusion Momentum offers cultural services and products in all disciplines of the performing arts including music, dance, theater, circus, and so on. These two

[2] culturemauricie.ca/
[3] https://www.lecarre150.com/

enterprises were chosen due to their wide variety of cultural products and services, which can be enhanced through the application of customer intelligence for the cultural sector. In addition, managers from these enterprises also express a strong motivation in applying customer intelligence for marketing benefits. Culture Mauricie aims at improving the diffusion and recommendations of cultural products for customers whereas Diffusion Momentum yearns for taking advantage of customer intelligence to improve customer satisfaction and boost sales.

Table 1.3
Profiles of cultural organizations in Québec

Period	**Organizations**	**Enterprise profiles**
09-12/2019	Diffusion Momentum	**Domain:** Show broadcaster **Main products:** Music shows, concerts, circus, theatre, and dancing performances.
01-12/2020	Culture Mauricie	**Domain:** Culture and arts **Main products:** Events and products related to visual arts, performing arts, literature, media arts, museums, and heritage.

Source: Dam (2020)

Culture Mauricie and Diffusion Momentum have a wide variety of data that can be acquired from websites, Facebook, Google Analytics, and internal sources. Especially, Cultural Mauricie with a network of more than 400 members has valuable data sources that can be transformed into customer intelligence. This indicates a great opportunity for these cultural organizations to take advantage of customer intelligence for marketing benefits.

Regardless of diverse data sources, Culture Mauricie and Diffusion Momentum face the challenges of data integration and analytics to convert data into customer intelligence. Managers at cultural organizations often lack analytic and information technology (IT) skills to integrate and interpret data to support the decision-making process. However, they showed a great vision in adopting customer intelligence for marketing benefits. Several projects have been implemented to promote the application of customer intelligence. This stimulates and reinforces the motivation of choosing the cultural sector as the field of study for this thesis.

1.3.2 Findings from residence in enterprises

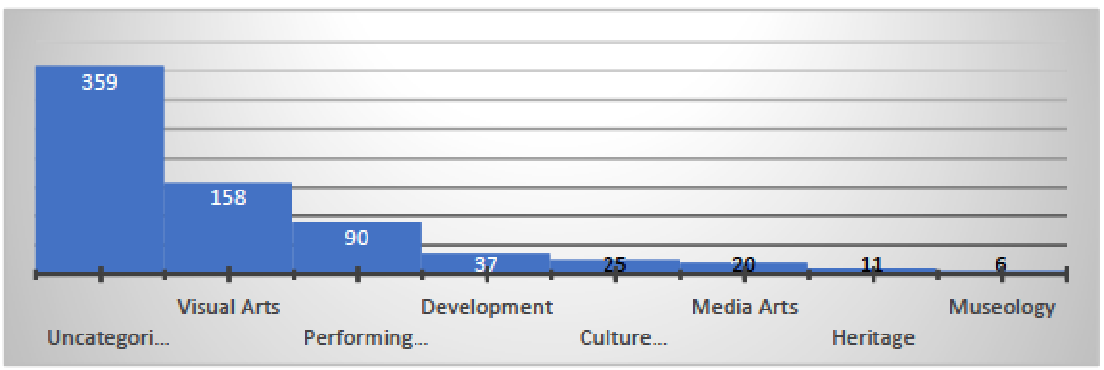
With the motivation to learn about the reality of how customer intelligence is applied at these enterprises, the author has adopted different data collection techniques such as documentary analysis, interviews, and observation during the residence in enterprises. As Vietnamese export enterprises are not ready for adopting customer intelligence, this section focuses on findings from the residence in cultural organizations in Quebec, Canada. In this light, several findings are revealed with relevance to big data analytics and customer intelligence for marketing benefits.

1.3.2.1 Big data analytics

This part presents findings related to big data analytics in the setting of the cultural sector in Quebec, Canada. Firstly, the big picture of the cultural sector in Québec, Canada is portrayed so that readers can understand the characteristics of the sector. Then the digital gaps of cultural organizations reveal the current status-quo of cultural organizations in adopting big data analytics. Accordingly, challenges in big data integration and analytics are discussed in detail.

Intending to bring together people and organizations that contribute professionally to the artistic and cultural life of Mauricie, Culture Mauricie has a strong network with more than 400 members who are professional artists and cultural organizations/enterprises in the local region. According to statistical data from Figure 1.1, the majority of cultural SMEs/SMOs belong to the domain of Visual Arts (158 SMEs/SMOs), followed by Performing Arts (90 SMEs/SMOs). Most professional artists identify themselves as Development (37 artists) or Culture Professionals (25 artists). Development can be considered as organizations or individuals who are dedicated to the defense and promotion of culture. Culture Professionals are described as individuals or groups who exercise a profession in the arts and culture, particularly in architecture, animation, design, teaching, management, graphics, illustration, media, communications, etc. A small number of cultural SMEs/SMOs categorize themselves in the domains of Media Arts (20 SMEs/SMOs), Heritage (11 SMEs/SMOs), and Museology (6 SMEs/SMOs). It is also necessary to consider 359 members of Culture Mauricie who do not identify themselves in any cultural domains.

Figure 1.1
Categorization of cultural domains in Québec, Canada



Source: Culture Mauricie (2019)

Even though these cultural SMEs/SMOs including Culture Mauricie and Diffusion Momentum express an interest in applying customer intelligence from the availability of data, the majority of them (nearly 40%) do not own either a Web page or social media page. According to Table 1.4, 55.67% of Culture Mauricie's members have a Web page while 4.53% of them only own a social media page such as Facebook, Myspace, YouTube, and Instagram. There is a possibility that Culture Mauricie's members can own both a webpage and social media pages. For the 55.67% of cultural SMEs/SMOs with a Web page, log files and clickstream data would be a great source for customer intelligence. On the other hand, cultural SMEs/SMOs can analyze data on views, shares, comments, likes, and so on from social media pages.

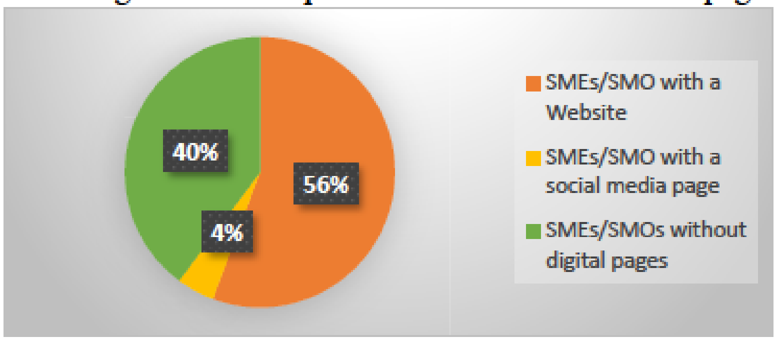
Table 1.4
Statistics on webpages and social media pages

	Number	**Percentage**
SMEs/SMO with a Web page	393	55.67%
SMEs/SMO with a social media page	32	4.53%
SMEs/SMOs without digital pages	281	39.80%
Total SMEs/SMOs	706	100.00%

Source: Culture Mauricie (2020)

Similar to Diffusion Momentum, Culture Mauricie faces the challenge of integrating customer data from diverse sources. The website of Culture Mauricie does not keep track of cultural consumption and customer subscription. Data on customers and products scatter over personal Facebook pages, histoirequebec.qc.ca, lepointdevente.com, and other third parties. From the management dimension, it is challenging for Culture Mauricie to make accurate predictions on customer trends and preferences due to the challenges of data capturing and integration. From the customer dimension, the challenge of customers has changed from information shortage to information overload (Sassi et al., 2017). Customers address the challenge of filtering out misleading information and efficiently searching for the right products and services (Ekstrand et al., 2011; Schafer et al., 2007; Wedel & Kannan, 2016). Therefore, dealing with problems relevant to big data for customer intelligence is beneficial for both enterprises and customers.

Figure 1.2
Percentage of ownership of websites and social media pages



Source: Culture Mauricie (2020)

Diffusion Momentum and Culture Mauricie reveals many interesting facts on big data for customer intelligence. Managers at these organizations received several reports with precious data on sales and customers from ticket offices, the website, and other social media pages (Figure 1.2). However, they encounter the challenge of integrating and analyzing different sources of customer data for better data-driven decisions. Even though customer data are available from various sources, the integration of customer data is still an unsolved puzzle. This is in line with the findings from many previous studies (Baesens et al., 2016; Janssen et al., 2017; Leeflang et al., 2014). Furthermore, managers at Diffusion Momentum and Culture Mauricie struggled with analyzing customer data to predict the number as well as the distribution time and channels for advertising brochures. Therefore, they attempted to analyze customer data to improve marketing decisions for promotion strategies. Regarding analytics, managers seemed to do well with descriptive analytics through the support of simple dashboards from Google Analytics or functions from Microsoft Excel to explore historical and current data. They are unable to gain deeper insights into customer data due to the lack of a profound background in analytics. Dealing with predictive and prescriptive analytics brought more challenges to managers. This finding is also confirmed in the studies of Baesens et al. (2016); Mikalef et al. (2019); Wamba et al. (2017).

1.3.2.2 Customer intelligence for marketing benefits

This part presents findings from the residence in enterprises with relevance to customer intelligence marketing. In the same vein, the application of customer intelligence for marketing benefits at Culture Mauricie and Diffusion Momentum is presented. In addition, the residence uncovers the potential of customer intelligence for other cultural organizations.

A common finding found at Culture Mauricie and Diffusion Momentum is that customer intelligence is rarely applied to develop services or service-based products. While Diffusion Momentum shows little interest in service or service-based product development, Culture Mauricie is overwhelmed to make use of customer intelligence for recommendation service to improve the discoverability of cultural offerings. Discoverability (Boisnard et al., 2019) is defined as the ability of cultural products to be found by customers, who search for them and to be recommended to those who are unaware of them. The discoverability of cultural offerings is improved through the adoption of a recommender system that acquires and applies customer intelligence to suggest relevant items for specific customers. The manager of Culture Mauricie also stressed the importance of customer intelligence for recommendation service considering data related to the contexts and preferences of users.

In fact, not only Culture Mauricie and Diffusion Momentum attempt to take advantage of customer intelligence by offering services to achieve marketing benefits. The Québec Digital Cultural Plan (PCNQ), whose objective is to help cultural communities invest in digitalization to benefit Quebec and remain competitive in global markets, points out similar needs for customer intelligence to offering services from other regional SMEs/SMOs in the cultural sector[4]. Accordingly, the research on 80 cultural organizations and enterprises of PNCQ including Culture Mauricie, Culture Trois-

[4] http://www.stat.gouv.qc.ca/statistiques/culture/etat-lieux-metadonnees.html

Rivières, Culture Numérique, Synapse C, LATICCE, Culture Shawinigan, and so on face the problem of improving the discoverability of their products to meet target profits regardless of the tremendous amount of data. In accordance with this view, various studies have reinforced the importance of customer intelligence for offering services to help cultural SMEs/SMOs in Québec maintain competitive advantages (Bartolini et al., 2016; Moreno et al., 2013).

1.4 THE CULTURAL SECTOR AS THE FIELD OF STUDY

The findings from the residence in enterprises coupled with the literature review have strengthened the motivations for choosing the cultural sector as the field of study. Regardless of challenges from the nature of SMEs/SMOs, organizations in the cultural sector have shown great potential for customer intelligence adoption in terms of diverse sources, capabilities, a strong vision, and leadership. The most important thing is that the managers and directors have foreseen the potential and importance of customer intelligence for marketing benefits in this sector. With an intent to clarify such implications, this section also scrutinizes the importance of customer intelligence to the cultural sector.

1.4.1 Motivations for choosing the cultural sector

This section presents the motivations for choosing the cultural sector with respect to big data and analytics, customer intelligence for marketing benefits, and the nature of SMEs/SMOs. These motivations, which were summarized in Table 1.5, result from the residence in enterprises combined with the review of the literature.

Table 1.5
Summary of research motivations

Challenges	**Residence in Enterprises**	**Literature Review**
Big data and analytics	- Wide variety of data sources - Limited analytic capability - Challenges in data integration and analytics - Digital gap	- Potential data from customer interactions with enterprises and other customers - The digitalization of cultural organizations
Customer intelligence for marketing benefits	- Discoverability of cultural products - Customer satisfaction - Product/service development and innovation - Sustainable development	- Customers find it challenging to find the right products - Importance of services in the consumption of cultural products.
The nature of SMEs/SMOs	- Limited human and financial resources - Vision and leadership for customer intelligence adoption	- Insufficient funding - Conflict between commerce and arts

Source: Dam (2021)

The residence in enterprises revealed the great data sources of customer intelligence at cultural SMEs/SMO. This triggers the motivation to study the adoption of customer intelligence in the cultural sector. Another interesting point to ponder is that customers in the cultural sector tend to interact with artists or cultural SMEs/SMOs to learn more about the arts (Colbert, 2017; Rentschler, 2002). This is due to the fact that customers' perception of arts relies on guidance from critics and culture SMEs/SMOs (Colbert & Dantas, 2019; Rentschler, 2002). The cultural sector also appreciates the role of customers in co-producing or co-creating cultural products and services as the customer co-creation practice shortens the distance between customers and artworks (Colbert & Dantas, 2019; Ruiz et al., 2017). Additionally, cultural customers also interact with each other and form a community to educate themselves about arts, especially about brand positioning, understanding, and authenticity of cultural contents (Colbert, 2017; Katz-Gerro, 2004). Therefore, user-generated data from customer interactions in the cultural sector show great potential for the big data source. Regarding analytics, the residence in enterprises highlights the limited analytic capability of cultural SMEs/SMOs in integrating and analyzing data. It also indicated the digital gaps among organizations in the cultural sector. This is also in accordance with findings from the literature review which implies that the majority of SMEs/SMOs in the cultural sector are not digitalized (Filip et al., 2015; Ruiz et al., 2017). Taking a look at the European cultural sector, only 10% of European arts and cultural products are digitalized even though this sector is considered a great source of income for European SMEs/SMOs (Ciurea & Filip, 2016; Cooke & De Propris, 2011). However, limitations with data analytics can be overcome by the digital revolution which sparks the proliferation of mobile technology, augmented reality, cloud computing, big data analytic tools to support cultural SMEs/SMOs in dealing with this issue (Ciurea & Filip, 2016; Colbert & St-James, 2014). The successful application of information technologies in the cultural sector is promised to preserve cultural values, valorize artistic work, and enhance financial performance for cultural SMEs/SMOs (Filip et al., 2015; Garnham, 2005).

As unveiled in the residence in enterprises, Culture Mauricie and Diffusion Momentum aim at applying customer intelligence to achieve marketing benefits on customer satisfaction, product/service development, innovation, and recommendation. In accordance with this view, the literature indicates that customers find it challenging to discover cultural products that they need regardless of information overload in the age of big data (Ekstrand et al., 2011; Schafer et al., 2007; Wedel & Kannan, 2016). Literature also gives prominence to the importance of services in the consumption of cultural products (Ciurea & Filip, 2016; Dai et al., 2019; Filip et al., 2015). In the cultural sector, customers not only care for the core products but also yearn for service that satisfies their real needs (Boorsma, 2006; Vargo & Lusch, 2008). The study of Boivin and Tanguay (2019) in the case of Quebec City indicates services as a means to attract cultural consumers. For example, Quebec City took into consideration the means of transportation and friendly service to stimulate visitors' interests and increase their satisfaction. Therefore, the applications of customer intelligence would yield fruitful outcomes for the cultural sector.

Both literature review and residence in enterprises agree on the human and financial limitations of SMEs/SMOs. Literature also points out the challenge of insufficient funding for cultural SMEs/SMOs (Butler, 2000; Colbert, 2003). The cultural sector receives fewer fundings and supports compared to other sectors (Selwood, 2001). Fewer fundings may cause difficulty for the management dimension concerning the preservation, improvement, and dissemination of cultural products (Camarero et al., 2011). However, it is not necessarily true that these limitations can stop SMEs/SMOs from adopting customer intelligence. As a matter of fact, managers at cultural SMEs/SMOs have a strong vision and leadership for customer intelligence adoption as they can foresee the opportunities and benefits from customer intelligence. One of the typical nature of SMEs/SMOs in the cultural sector is the conflict between arts and commerce (Lee & Lee, 2017). As a matter of fact, artists or cultural content creators tend to produce products and services based on their passions and interests while lacking consideration in responding to consumer needs and preferences (Colbert & Dantas, 2019; Ruiz et al., 2017). The adoption of customer intelligence would help cultural SMEs/SMOs deal with this issue as customer intelligence empowers managers to make decisions based on data instead of their intuition.

1.4.2 Importance of customer intelligence for the cultural sector

To reinforce the motivations for choosing the cultural sector as the field of study, this section continues to examine the importance of customer intelligence for cultural SMEs/SMOs. The adoption of customer intelligence for the cultural sector promises to yield fruitful outcomes. The key importance of customer intelligence to cultural SMEs/SMO is presented as follows.

Advancements in technology enable cultural SMEs/SMOs to connect with customers (Filip et al., 2015; Haugstvedt & Krogstie, 2012). However, enterprises need to take advantage of customer intelligence to understand customer insights instead of paying too much attention to technological upgrades (McGrath & McManus, 2020; Newman, 2018). Technology is just a means for acquiring customer intelligence to develop and innovate services and service-based products to ensure success for enterprises (Lafrenière, 2020; McGrath & McManus, 2020). Integrated from diverse sources of data, customer intelligence can reveal attributes of customer behaviors along with changes in their preferences. The application of customer intelligence in the development and innovation of services and service-based products would yield profitable outcomes. In particular, as the characteristics of cultural events or sites require customers to get connected through the mobile platform for guidelines and information, real-time data related to geography, demography, behavior, and even physiology would serve as a great source for customer intelligence for improving services (Ciurea & Filip, 2016; Tscheu & Buhalis, 2016). Analyzing and applying these real-time data would reveal deep insights into customers and offer services and service-based products relevant to the context of customers (Ciurea & Filip, 2018; Filip et al., 2015). For example, customer intelligence is applied in developing context-aware recommender systems to make relevant recommendations on cultural products and services in the field of cultural heritage, tourism, and leisure activities (Bartolini et al., 2016; Moreno et al., 2013).

Given the primary role of marketing is to manage and transfer artistic values of cultural products/services to the public (Bartolini et al., 2016; Botti, 2000), customer intelligence would accelerate the speed of diffusing cultural contents. The way that customers respond to artworks does not rely on artists; instead, marketers offer the artistic service related to cultural products, for example, an ambiance, which manipulates the level of art appreciation and diffuses art values to the public (Butler, 2000; Colbert, 2014). Correspondingly, customer intelligence functions as the mechanism to stimulate and enhance optimal esthetic responses from customers when they interact with arts or cultural products.

Cultural SMEs/SMOs are under pressure to call for grants from the government and political parties to support arts and cultural products/services for the community (Ciurea & Filip, 2016; Colbert, 2003). In fact, only a small number of people are interested in arts and cultural products/services. Therefore, cultural SMEs/SMOs aim at expanding their target audience, particularly potential audiences from non-consumers of arts. Consequently, customer intelligence plays a significant role in the cultural sector as it can help cultural SMEs/SMOs attract and expand potential markets. Once cultural SMEs/SMOs can gain insight into customers, they are more likely to satisfy their customer needs and expand target markets.

As the literature indicates the irrelevance between customer needs and cultural offerings, customer intelligence would be the optimal solution for cultural SMEs/SMOs to gain deep insights into customer behaviors, preferences, and trends (Ruiz et al., 2017; Sorjonen & Uusitalo, 2003). Thanks to customer intelligence, cultural SMEs/SMOs can satisfy customers' needs and improve their loyalty. Customer loyalty, which indicates the commitment and intention of customers for repurchases, relies on the satisfaction with the core product and service as well as the delivery process (Boorsma, 2006; Colbert & Dantas, 2019). Products and services derived from customer intelligence are proved to induce customer loyalty due to the high level of customer satisfaction. The more satisfied customers are, the more likely they are expected to spend. This indicates the greater lifetime value that customers can offer to enterprises (Zerbino et al., 2018; J. Z. Zhang et al., 2018).

To build long-term relationships with customers, it is important to offer cultural products and services that meet customers' needs (Lee & Lee, 2017; Ruiz et al., 2017). Customer intelligence empowers enterprises with customer orientation in which enterprises consider customer preferences for cultural offerings (Fillis, 2011; Lee, 2005). It is noted that customer intelligence also promotes product and service orientation with innovative offerings to attract and retain customers (Colbert & Dantas, 2019). In addition, customer intelligence equips cultural SMEs/SMOs with competitor orientation (Cacciolatti & Fearne, 2013; Sorjonen & Uusitalo, 2003). Therefore, cultural enterprises will be able to keep track of competitors' activities, anticipate competitors' strategies, and learn from competitors' products (Boorsma, 2006; Colbert & St-James, 2014). Customer orientation coupled with product/service orientation and competitor orientation sets a solid foundation for customer intelligence to support cultural SMEs/SMOs in managing customer relationships (Colbert & Dantas, 2019; Sorjonen & Uusitalo, 2003).

Service experience consists of activities and surrounding environments that can influence customer appreciation and emotion toward cultural products/services (Colbert & St-James, 2014). As an illustration, the context of museums, the service environment, and the ambiance of performing arts can affect the aesthetic consumption and perceptions of customers (Filip et al., 2015; Haugstvedt & Krogstie, 2012). Customer intelligence can set a fertile ground for cultural SMEs/SMOs in understanding customer motivations and preferences towards cultural offerings (L. Rodner & Kerrigan, 2014; Lee & Lee, 2017).

As the literature indicates the irrelevance between customer needs and cultural offerings, customer intelligence would be the optimal solution for cultural SMEs/SMOs to gain deep insights into customer behaviors, preferences, and trends (Ruiz et al., 2017; Sorjonen & Uusitalo, 2003). Thanks to customer intelligence, cultural SMEs/SMOs can satisfy customers' needs and improve their loyalty. Customer loyalty, which indicates the commitment and intention of customers for repurchases, relies on the satisfaction with the core product and service as well as the delivery process (Boorsma, 2006; Colbert & Dantas, 2019). Products and services derived from customer intelligence are proved to induce customer loyalty due to the high level of customer satisfaction. The more satisfied customers are, the more likely they are expected to spend. This indicates the greater lifetime value that customers can offer to enterprises (Zerbino et al., 2018; J. Z. Zhang et al., 2018).

The cultural sector recognizes the roles of customers as co-producers and co-creators (Ruiz et al., 2017; Song et al., 2018). Due to the perceived distance between customers and artworks, customers tend to participate in the co-creation process to give meaning to cultural products/services (Colbert & St-James, 2014). Through this participation, customers can blur their distinction with art creators and leverage their cultural appreciation (Nakajima, 2012). On the other hand, cultural products/services are reconceptualized to bring arts and culture to the public (Colbert, 2014; L. Rodner & Kerrigan, 2014).

Customer intelligence can be applied to design and optimize customer journeys, which consist of *recognizing* customer needs, *requesting* a product or service that might meet their needs, and *responding* to the delivery of service and products (Siggelkow & Terwiesch, 2019). In other words, the three stages of recognizing, requesting, and responding represent the pre-purchase, purchase, and post-purchase of a customer journey (Rawson et al., 2013). Accordingly, service providers attempt to map customer journeys with key touchpoints in each stage (Stein & Ramaseshan, 2016). Identifying touchpoints is significant as they are interactive opportunities for potential customers to engage with service providers (Lemon & Verhoef, 2016).

The application of customer intelligence empowers SMEs/SMOs to boost financial performance and achieve substantial profit gains (Baesens et al., 2016; Cacciolatti & Fearne, 2013). In general, enterprises that take advantage of customer big data can outperform their competitors with 6% more profits (McAfee et al., 2012). Top-performing enterprises tend to apply customer intelligence to improve data-driven decisions (LaValle et al., 2011; Leeflang et al., 2014). Furthermore, customer intelligence which promotes the transformation of information technology is promised to be a strategic economic resource for cultural SMEs/SMOs (Ciurea & Filip, 2016;

Colbert & Dantas, 2019). As an illustration, the study of Ciurea and Filip (2016) reveals the increasing number of virtual exhibitions and online visitors which contribute to considerable revenues for cultural enterprises and organizations in the age of big data.

1.5 RESEARCH MOTIVATION

The synthesis of relevant articles coupled with findings from the residence in enterprises has strongly confirmed the managerial problems of customer intelligence in the age of big data. As presented in the previous part, these problems arise from big data analytics, the application of customer intelligence for marketing benefits, and the characteristics of SMEs/SMOs (Cacciolatti & Fearne, 2013; Chari et al., 2017; Liang & Liu, 2018). Overcoming these challenges is significant for enterprises to gain competitive advantages in today's fierce competition (Chianese & Piccialli, 2016; Colbert & Dantas, 2019; Yohn, 2018). Furthermore, the residence in enterprises also prompts the motivations for selecting the cultural sector as the field of study. The adoption of customer intelligence for marketing benefits would produce successful results for SMEs/SMOs in the cultural sector.

Building on these reflections, the thesis aims at studying customer intelligence for marketing benefits. Even though the research stream on customer intelligence is catching more interest from scholars, there is a small number of studies articulating this research topic (Chari et al., 2017; Davenport et al., 2020; Singh & Verma, 2014). Furthermore, the majority of research lacks the focus on the application of customer intelligence for marketing benefits (Lau et al., 2016; Li & Li, 2013; Liang & Liu, 2018). Considering the challenges and opportunities in adopting customer intelligence in the setting of cultural SMEs/SMOs, the thesis chose the cultural sector as the field of study. Therefore, the research motivation is to study customer intelligence and its applications for marketing benefits of enterprises, particularly cultural SMEs/SMOs, in the age of big data.

1.6 THE STRUCTURE OF THE THESIS

Figure 1.3 presents the structure of the thesis with detailed steps in each chapter. First of all, Chapter 1 examines the managerial problems in the context of customer intelligence for marketing benefits in the age of big data. The validation of the managerial problems at the residence in enterprises is also presented in this chapter. Based on the residence in enterprises, the author chooses the cultural sector as the field of study and defines the research motivation. Subsequently, the author conducts a systematic literature review in Chapter 2 to further investigate the research motivation. The literature review demystifies research gaps and identified important constructs related to customer intelligence. Based on the research gaps identified from the reviewed literature, Chapter 3 develops a conceptual model of customer intelligence for marketing benefits (CIMB) and proposes the research questions. Subsequently, Chapter 4 proposes the research design to further investigate these research questions. Based on the research design, Chapter 5 presents the research results and discussions based on the CIMB model in Chapter 3. Finally, Chapter 6 concludes with the contributions, future research directions, research limitations, and research ethics.

Figure 1.3
Structure of the thesis

Source: Dam (2021)

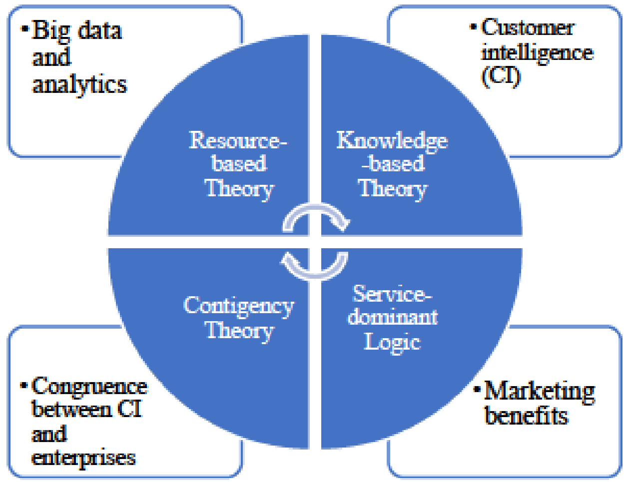
CHAPTER 2
LITERATURE REVIEW

Chapter 2 focuses on the literature review to further investigate the research motivations in Chapter 1. The literature review lays its profound foundation on the theories relevant to customer intelligence. In this chapter, the process of identifying and reviewing the selected articles is described to ensure the validity of the literature review. Afterward, the chapter presents the analysis of findings from the reviewed articles. Chapter 2 ends with a discussion of the research gaps based on the literature review.

2.1 THEORETICAL BACKGROUNDS

This section of the thesis addresses theories that serve as an anchor for the literature review of this research. As illustrated in Figure 2.1, the thesis lays its foundation on the resource-based view (Barney, 1991), the knowledge-based view (Grant, 1996), the contingency theory (Lawrence & Lorsch, 1967), and the service-dominant logic (Vargo & Lusch, 2004). The resource-based theory supports big data and analytics as resources and capabilities (Barney, 1991) whereas the knowledge-based theory enhances the role of customer intelligence as knowledge (Grant, 1996). The contingency theory examines the congruence between customer intelligence and enterprises. Finally, the service-dominant logic (Vargo & Lusch, 2004) adds value to the application of customer intelligence for marketing benefits.

Figure 2.1
Theories supporting the literature review of the thesis



Source: Dam (2021)

2.1.1 Resource-based theory

The resource-based theory supports big data as resources and analytics as capabilities for enterprises to create value from such resources (Barney, 1991). This part provides an overview of the resource-based theory and then discusses the role of big data and analytics as resources and capabilities.

This study relies on the resource-based theory (Barney, 1991) as this theory is well adopted by many researchers in explaining the key to success for enterprises (Kozlenkova et al., 2014; Rakthin et al., 2016). Resources, which are defined as internal "assets, capabilities, organizational processes, firm attributes, information, knowledge, etc.", play the ultimate role in the strategic planning for success (Barney, 1991). These resources require enterprises' capabilities (Grant, 1991) to turn them into core competencies (Prabalad & Hamel, 1990). Capabilities are the abilities of enterprises to acquire knowledge and skills from resources to leverage resource values. Capabilities can be perceived as implied ability or intangible resources whereas competencies are considered as improved and proven capabilities (Kozlenkova et al., 2014; Rakthin et al., 2016). Competencies are defined as subcategorized, firm-specific, and non-transferable resources. Competencies play an important role in improving the productivity of other resources (Kozlenkova et al., 2014; Prabalad & Hamel, 1990). It is vital to identify an enterprise's resources (Grant, 1991) and key competencies to stand out from the competition (Prabalad & Hamel, 1990). The findings from the study of Barney (1991) point out four attributes of resources as indicators for a sustainable competitive advantage: value, rareness, imperfect imitability, and non-substitutability.

According to the resource-based theory (Barney, 1991), enterprises possess a wide variety of resources, including human resources, technology, infrastructure, databases, etc. From the perspective of customer intelligence, big data are considered a substantial resource for enterprises (Efrat et al., 2017; Navarro-García et al., 2016). However, data are useless if they are not integrated, analyzed, and converted into customer intelligence through the support of analytics (LaValle et al., 2011; Lies, 2019). The transformation from data into customer intelligence requires the capabilities of enterprises such as managers' analytic skills along with the configuration of human resources, customer data, and technology (LaValle et al., 2011; Mikalef, Krogstie, et al., 2020; Mikalef et al., 2019). The more these capabilities correspond to the four characteristics of resources, including valuable, rare, difficult to imitate, and non-substitutable; the more sustainable competitive advantages are. Accordingly, the capabilities to analyze and interpret customer data are valuable and rare as not many managers can have such analytic skills. It is also difficult to imitate or replace this competency. Therefore, managers with better analytical skills are more likely to turn customer data into intelligence.

2.1.2 Knowledge-based theory

The knowledge-based theory by Grant (1996) supports the role of customer intelligence as knowledge acquired from big data and analytics. The section presents an overview of the knowledge-based theory and discusses customer intelligence from the lens of this theory.

As an inheritance and development from the resource-based theory (Barney, 1991), the knowledge-based theory (Grant, 1996) perceives an enterprise as an institution for the integration of tacit and explicit knowledge. Explicit knowledge is easily documented, structured, and transferable whereas tacit knowledge is implicit, hidden, and difficult to transfer within an enterprise (Grant, 1996; Nonaka, 1994). An example of explicit knowledge would be databases, manuals, or reports that can be shared within enterprises (Alavi & Leidner, 2001; Grant, 1996). Conversely, tacit knowledge such as experience, skills, or mental judgment resides in the minds of managers and employees (Alavi & Leidner, 2001; Paarup Nielsen, 2006). Customer intelligence can be perceived as explicit knowledge, which is structurally stored and visualized (Amado et al., 2018; Anshari et al., 2019). On the flip side, experience, analytics, and relevant skills of managers and employees can be labeled as tacit knowledge (Chevallier et al., 2016; Khan & Vorley, 2017). Customer intelligence will be implicit unless it is applied to develop rules, instructions, and procedures as directive tasks, business processes as organizational routines (Grant, 1996), or product/service innovation (Bose, 2008; Fan et al., 2015).

As knowledge is constituted from knowledge objects, a knowledge object contributes to the development of structured sets of data, information, insights, or intelligence (Bellenger, 2004; Rowley, 2007) that is related to a specific business area. The knowledge development process starts with data, evolving into information and insights, then reaching the highest level of intelligence. *Data* are defined as raw and unprocessed numbers or text (Erevelles et al., 2016; Hu et al., 2014). Once data are processed, aggregated, and organized, they become *information*. *Insights* are the presentation of information used in an organization, through the reflection of business rules, models, and dashboards with relevance to a particular context or phenomena (Holmlund et al., 2020; Yohn, 2018). In this thesis, *intelligence* is considered as the highest hierarchy of data transformation. *Intelligence* is the ability to perceive and apply *insights* to the decision-making process to overcome a business situation (Dinh & Dam, 2021).

2.1.3 Contingency theory

The contingency theory (Lawrence & Lorsch, 1967) reinforces the resource-based theory (Barney, 1991) and the knowledge-based theory (Grant, 1996) by focusing on the congruence between internal and external factors. This section presents an overview of the contingency theory and discusses the congruence between customer intelligence and enterprises.

The contingency theory is applied in many studies related to marketing intelligence in general and customer intelligence in particular (Heiens & Pleshko, 2011; Magnusson et al., 2013; Wright & Ashill, 1998). In this light, the contingency theory affirms that enterprises are dependent on both internal and external factors (Lawrence & Lorsch, 1967). Internal conditions can be firm size, technology, and employees whereas the external factors consist of the economy, environmental uncertainty, market, and so on (Heiens & Pleshko, 2011; Lawrence & Lorsch, 1967; Magnusson et al., 2013). According to the contingency theory, the organizational structure of enterprises should be compatible with the external environment as it is impossible to design a perfect organization (Galbraith, 1973; Lawrence & Lorsch, 1967). In essence, the success of enterprises relies on the congruence or fit between the organizational structure and environmental factors (Lawrence & Lorsch, 1967). For instance, an enterprise's marketing strategy needs to be aligned with the market orientation of the target market to achieve higher revenues (Heiens & Pleshko, 2011).

Through the lens of the contingency theory, customer intelligence is perceived as an important environmental factor that enterprises should consider as an indicator of success (Reim et al., 2019; Whalen et al., 2016). Many studies reach an agreement on this point of view by confirming the interdependency between enterprises and customers (Preikschas et al., 2017; Ramaswamy & Ozcan, 2014). Enterprises rely on customers as an input of customer intelligence for product/service development and innovation (Ramaswamy & Ozcan, 2018; Saarijärvi et al., 2013). On the other side, customers tend to interact with enterprises to improve their experience with products/services and to gain economic benefits (Ramaswamy & Ozcan, 2016; Tu et al., 2018). To better stimulate customer intelligence from the customer-enterprise interaction, the organizational structure has to be congruent with customers through the provided interactive platforms and attractive benefits (Fernandes & Remelhe, 2016; Galvagno & Dalli, 2014). In summary, the contingency theory reinforces the role of customer intelligence from the external environment along with the congruence between customers and organizational structure (Heiens & Pleshko, 2011; Reim et al., 2019; Whalen et al., 2016). Enterprises will make a huge mistake if they ignore this external contingency (Galbraith, 1973; Lawrence & Lorsch, 1967).

2.1.4 Service-dominant logic

In accordance with the contingency theory, the service-dominant (S-D) logic gives prominence to external actors (Vargo & Lusch, 2004). This section presents an overview of the S-D logic and discusses marketing benefits from the lens of service-dominant logic.

The S-D logic holds significant implications for *service* as "the fundamental basis of exchange" to facilitate mutual interests between external actors and enterprises (Lusch & Vargo, 2006). Laid the foundation upon the service-dominant logic, the thesis follows the definition of *service* as "a *process* of doing something for and with another party" instead of *services* as "*units of output*" from the product-dominant logic (Vargo & Lusch, 2008). As a collaborative process, service is the application of knowledge and skills – which are also called *competences* – to offer benefits for service providers and beneficiaries (Vargo & Lusch, 2004). The ultimate goal of the S-D logic is to leverage the value of both products and *services* - "units of output"- through *service,* the process to advance mutual interests. Therefore, the S-D logic sets a strong service-based foundation for all economic activities, including physical or tangible products (Lusch & Nambisan, 2015). In fact, the service-dominant logic has penetrated many industries, including tangible and intangible products, and become a key indicator of competitive advantages (Frow et al., 2015; Vargo & Lusch, 2017).

Customers are highlighted as co-creators of value through interactivities with service providers (Jouny-Rivier et al., 2017; Lusch & Nambisan, 2015). The S-D logic gives prominence to the *operant resources* of customers - which are intangible and dynamic such as knowledge and skills - as the primary source of marketing benefits (Vargo & Lusch, 2016). Accordingly, enterprises will take advantage of the *operant resources* of customers to offer marketing benefits to other customers (Vargo & Lusch, 2017). To put it another way, the service-dominant logic clarifies and emphasizes the role of customers to help enterprises understand customer behaviors and offer marketing benefits to advance mutual interests between customers and service providers (Ranjan & Read, 2019).

2.1.5 Summary of theories

The analysis of the four theories relevant to customer intelligence strengthens the significance of customer intelligence as a substantial resource of knowledge from the external environment. These theories also emphasize the importance of the congruence between an enterprise and external factors for achieving marketing benefits.

Each theory supports different perspectives of customer intelligence. Table 2.1 resumes the main implication of the four theories for customer intelligence. Firstly, the resource-based theory (Barney, 1991) explains big data as a source of customer intelligence while clarifying analytic capabilities for turning resources into sustainable competitive advantages. Secondly, the knowledge-based theory (Grant, 1996) accentuates the role of customer intelligence in the hierarchy of knowledge. Thirdly, the contingency theory (Lawrence & Lorsch, 1967) defines how enterprises depend on external factors, especially the congruence between customer intelligence and enterprises. Finally, the service-dominant logic (Vargo & Lusch, 2004) studies the significance of service as an economic exchange to optimize marketing benefits for customers.

Table 2.1
Theories and customer intelligence (CI)

Theories	**Key assumptions**	**Variables to observe**	**Implications for CI**	**Reference**
Resource-based	- Resources are assets, capabilities, organizational processes, firm attributes, information, and knowledge. - Capability is the ability to acquire knowledge and skills from resources. - Competency is the improved and proven capability. - Important characteristics of resources: value, rareness, imperfect imitability, and non-substitutability.	- Internal resources - Capability - Competency	- Big data as a significant resource. - Big data analytics as a capability.	Barney (1991); Grant (1991); Kozlenkova et al. (2014); Prabalad and Hamel (1990); LaValle et al. (2011).
Knowledge-based	- Enterprise as an institution for knowledge. - It is difficult to acquire tacit knowledge. - The role of customer intelligence in the hierarchy of knowledge	- Explicit knowledge - Tacit knowledge	- Customer intelligence as explicit knowledge. - Experience, analytics, and skill as tacit knowledge.	Grant (1996); Alavi and Leidner (2001); Nonaka (1994); Paarup Nielsen (2006); Amado et al. (2018).
Contingency	- Enterprises are dependent on both internal and external factors. -The congruence or fit between the organizational structure and environmental factors.	- Internal factors - External factors - The congruence	- External factors: customers, customer intelligence. - Congruence via organization al structure, interactive	Lawrence and Lorsch (1967); Galbraith (1973); Heiens and Pleshko (2011); Reim et al. (2019); Whalen et al. (2016); Wright and Ashill (1998)

Theories	Key assumptions	Variables to observe	Implications for CI	Reference
			platforms, benefits.	
Service-dominant	- *Service* as the fundamental basis of exchange. - *Service* as a *process* of doing something for and with another party to advance mutual interests. - *Service* is the application of knowledge and skills called competences.	- Service - Collaborative process - Competences - Mutual interests - Operant resources	- Operant resources of customers are knowledge and skills - Marketing benefits for customers.	Lusch and Vargo (2006); Lusch et al. (2008); Vargo and Lusch (2004, 2008, 2016, 2017).

Source: Dam (2020)

2.2 LITERATURE REVIEW

To ensure a comprehensive literature review, the thesis follows the systematic approach by Webster and Watson (2002) and Okoli and Schabram (2010) as shown in Figure 2.2. Accordingly, the processes of identifying the relevant literature, reviewing the relevant literature, and analyzing findings is presented. This section focuses on the two first steps of this process then the analysis of findings is presented in the following part of the thesis.

Figure 2.2
A systematic guide to literature review development

Source: Adapted from Okoli and Schabram (2010); Webster and Watson (2002)

2.2.1 Identification of the relevant literature

The identification of relevant literature aims at searching the literature, filtering with inclusion and exclusion criteria, and screening the literature to identify the most relevant articles.

Searches are conducted in various databases including Scopus, Science Direct, Emerald Insight, SpringerLink, ProQuest, and Google Scholar (Levy & Ellis, 2006; Webster & Watson, 2002). Different keywords such as "customer intelligence", "customer knowledge", "customer information", "customer insight", and "customer intimacy" are used to look for articles from these databases. Being aware that customer intelligence is generated from customer-customer and customer-enterprise interactions, other terms that are strongly related to customer intelligence such as "customer interaction", "customer co-creation", and "customer collaboration" are also used to identify relevant articles. The search results in approximately 27,997 hits. Table 2.2 provides the detail on the number of hits in each database.

The inclusion and exclusion criteria are applied to filter out relevant articles. Assuming the majority of research on customer intelligence is written in English, only publications in this language are chosen. The period from 2000 to 2020 is applied to filter out articles as it is broad enough to view changes in the research stream of customer intelligence. Other inclusion and exclusion factors are peer-reviewed criteria and research approaches. Articles that are not peer-reviewed are excluded. The selected articles are limited to studies that are conducted from the approach of service-dominant logic. Publications that only mention the search keywords a couple of times and lack focus on the topic are not considered. Finally, the selected literature is also chosen with relevance to the cultural sector. Considering the very limited number of publications on customer intelligence in the cultural sector, the reviewed literature includes but is not limited to relevant articles in the cultural sector. After the inclusion and exclusion process, about 2268 hits remain.

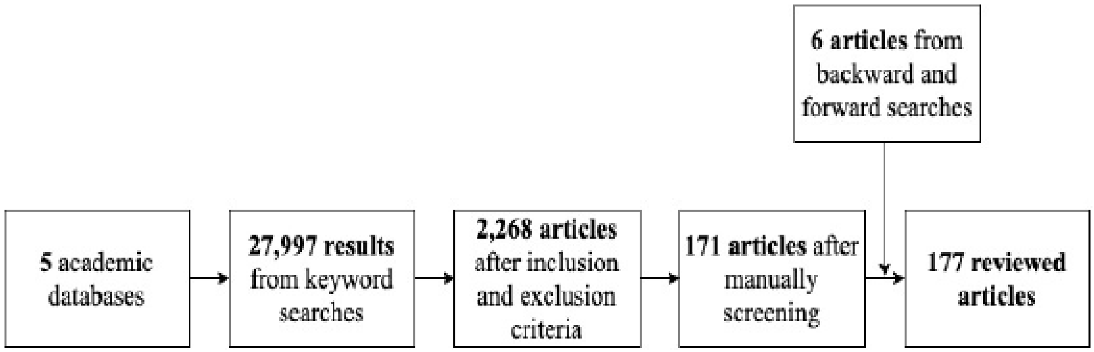
Table 2.2
Number of hits in the databases

Database	**Results by Keyword search**	**After inclusion and exclusion criteria**	**After manually screening**
Scopus	928	452	29
Google Scholar	24459	986	52
ScienceDirect	1210	215	38
Emerald Insight	946	457	35
SpringerLink	454	158	25
Total	**27997**	**2268**	**177**

Source: Dam (2021)

The notion of customer co-creation, which emphasizes the focus of the thesis on customer intelligence is applied to get rid of irrelevant publications. Furthermore, the selected articles are also qualified for the definition of *service* as "*the process* of doing something for and with another party" from the S-D logic and service science. Publications considering *services* as "*units of output*" from the product-dominant (P-D) logic are, therefore, excluded. This reduction step ends with 171 most relevant articles. To ensure the validity and reliability of the literature review, a backward and a forward search are also implemented to avoid missing relevant publications (Webster & Watson, 2002). The backward search examines the reference and keywords of the reviewed articles while the forward search focuses on related work after the publication of an article. The backward and forward search ends the process of identifying relevant literature with a total of 177 articles. All steps in identifying the relevant literature review are illustrated in Figure 2.3.

Figure 2.3
The process of identification of the relevant literature



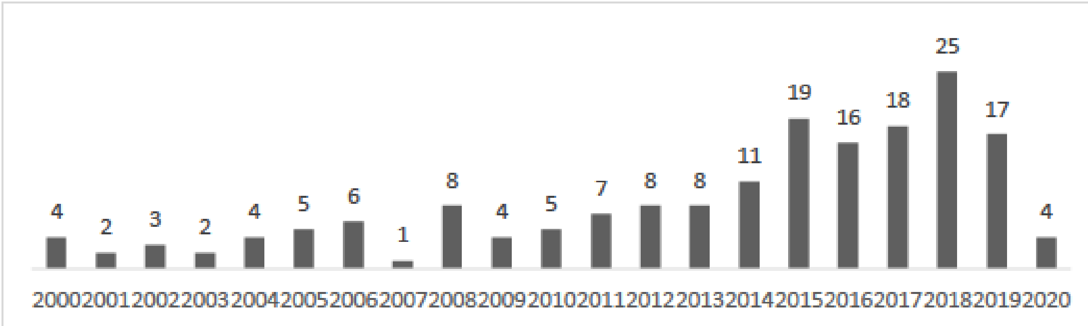
Source: Dam (2021)

2.2.2 Review of the relevant literature

The process of reviewing the relevant literature focuses on categorizing and analyzing selected articles to identify correlated concepts, gaps, and trends in customer intelligence (Okoli & Schabram, 2010; Webster & Watson, 2002). Consequently, this section presents the categorization of the relevant literature by year of publication and journal titles.

The categorization of reviewed articles by years of publication is demonstrated to catch trends and reveal the change in traditional customer marketing compared to data-driven customer intelligence in the age of big data. Figure 2.4 illustrates the year of publication from 2000 to 2020. It can be seen that the number of articles discussing customer intelligence has significantly increased over the past ten years, especially from 2015 to 2019. Not many articles were published before 2010. The research stream is catching more attention from scholars. This indicates the importance and relevance of customer intelligence in the modern economy.

Figure 2.4
Year of publication of the relevant literature



Source: Dam (2021)

As the searching process for relevant literature is conducted in different databases, the number of academic journals is diverse. Articles are selected from journals in different domains, including Business Management, Art Management, Marketing, Cultural Policy, Service Science, Information Systems, Hospitality Management, and so on. Table 2.3 summarizes the list of journals along with the number of selected articles. It can be seen that a significant proportion of selected articles comes from Harvard Business Review (6.8%), Journal of Business Research (6.2%), Industrial Marketing Management (2.8%), followed by International Journal of Cultural Policy (2.3%), and MIT Sloan Management Review (2.3%). Other journals that are also well-referenced are Expert Systems with Applications (2.3%), Service Science (1.7%), and Psychology & Marketing (1.7%). It is noticeable that even though the research stream of customer intelligence is catching the attention of scholars, the number of articles from journals in culture and art management is still limited. This strengthens the research objectives in conducting a comprehensive literature review on customer intelligence for marketing benefits with a focus on SMEs/SMOs in the cultural sector.

Table 2.3
Distribution of publications by journal titles

Journal Title	**Quantity**	**Percentage**
Journal of Business Research	11	6.2%
Harvard Business Review	12	6.8%
International Journal of Arts Management	5	2.8%
International Journal of Contemporary Hospitality	2	1.1%
Management	4	2.3%
International Journal of Cultural Policy	4	2.3%
Expert Systems with Applications	3	1.7%
Information & Management	8	4.5%
Journal of Service Management	5	2.8%
Journal of the Academy of Marketing Science	2	1.1%
Journal of Service Theory and Practice	3	1.7%
MIS Quarterly	4	2.3%
MIT Sloan Management Review	3	1.7%
Service Science	3	1.7%
Psychology & Marketing	5	2.8%
Industrial Marketing Management	1	0.6%
International Journal of Research in Marketing	102	57.6%
Others		
Total	177	100%

Source: Dam (2021)

2.3 ANALYSIS OF FINDINGS

This section presents the findings of analyzing the relevant literature. Firstly, the section clarifies changes in the definition of customer intelligence and proposes an updated definition to deal with the evolution of big data. Subsequently, the section focuses on the characteristics of customer intelligence through value, resources, and engagement forms to stimulate the process of co-creating customer intelligence. Finally, the section ends with the discussion of marketing benefits through the dimensions of management, science, and engineering of service science.

2.3.1 Definition of customer intelligence

The proliferation of customer big data along with the dominance of the service sector in the age of big data has changed the notion of customer intelligence (Im & Qu, 2017; Mikalef, Krogstie, et al., 2020). Considering these changes, the subsequent part re-defines customer intelligence with relevance to the age of big data.

Literature acknowledges different definitions of customer intelligence (Chevallier et al., 2016; Lies, 2019; Rakthin et al., 2016). Table 2.4 compares definitions of customer intelligence based on the three dimensions of the service science approach: science, management, and engineering (Maglio & Spohrer, 2013; Spohrer et al., 2007). As the majority of definitions of customer intelligence are outdated due to the big data revolution (Chen & Popovich, 2003; Gobble, 2015; Keskin, 2006; Rygielski et al., 2002; Sigala, 2011), there is a need for an updated definition of customer intelligence to adapt to changes in the big data revolution. In fact, the era of big data has reshaped the definition of customer intelligence (Davenport et al., 2020; Lies, 2019). The literature hardly recognizes an official definition of customer intelligence, especially a definition that can comprehensively cover the three dimensions of the service science approach (Gobble, 2015; Rakthin et al., 2016; Yan et al., 2020). The majority of research on customer intelligence concentrates on the management dimension with various streams, including customer target (Rygielski et al., 2002), innovation (Keskin, 2006; Lewrick et al., 2011), customer service (Guarda et al., 2012), customer experience (Singh & Verma, 2014), customer behaviors (Rakthin et al., 2016; Singh & Verma, 2014), customer relationships (Gobble, 2015), decision-making (López-Robles et al., 2019), and recommendations (Yan et al., 2020). Table 9 reveals that the majority of definitions of customer intelligence over the past 20 years lack focus on the science dimension. The studies by Keskin (2006) and Singh & Verma (2014) made a difference by highlighting the dimensions of organizational learning and the business process of customer intelligence. On the other side, the engineering dimension has witnessed the revolution from traditional Enterprise Resource Planning (ERP), and Customer Relationship Management (CRM) to big data platforms (Samuel, 2015; Stone et al., 2017). Customer intelligence is moving to a higher level thanks to the support of data mining techniques for the collaborative decision-making process (Gobble, 2015; López-Robles et al., 2019). Therefore, customer intelligence is capable of enhancing personalized customer experience through analytics and the excavation of big data (Yan et al., 2020). This forms the rationale for reshaping the definition of customer intelligence. Consequently, this part of the thesis aims at developing a state-of-the-art definition of customer intelligence in the age of big data.

According to the Oxford dictionary, intelligence is the "ability to acquire and apply knowledge and skills" (Dictionary, 2014). On the other hand, the American Association of Marketing (AMA) defines a customer as the "actual or prospective purchaser of products or services" (Association, 2015). The AMA also clarifies the role of marketing as "the activity, set of institutions, and processes for creating, communicating, delivering, and exchanging offerings that have value for customers, clients, partners, and society at large" (Rownd & Heath, 2008). In the digital age, the emergence of big data along with analytic techniques has made a significant impact on the definition of marketing and customer (Sutcliff et al., 2019; Tabrizi et al., 2019). As huge sets of data in terms of volumes, velocity, variety, veracity, and value, big data require the application of analytic techniques, including descriptive, predictive, and prescriptive to transform data into intelligence (Chen et al., 2012; Lau et al., 2016). Building on these reflections, this thesis reshapes the definition of customer intelligence in the age of big data as:

> Customer intelligence is the ability to acquire knowledge and skills from big data and business analytics and to apply them to the process of creating, communicating, delivering, and co-creating to offer more value to actual or prospective customers of services-based products or services.

Table 2.4
A comparison of customer intelligence

Reference	Science	Management	Engineering
Rygielski et al. (2002)		Customer targeting Product sales	CRM
Chen and Popovich (2003)	Business process	Understand customer behaviors	CRM, ERP
Keskin (2006)	Organizational learning	Innovation	
Lewrick et al. (2011)		Product innovation and development	
Guarda et al. (2012)		Customer service	Data system
Singh and Verma (2014)	Business Process	Customer experience Customer behaviors	
Samuel (2015)			Social media data
Gobble (2015)		Customer relationships Decision-making	
Rakthin et al. (2016)		Customer needs Buying decision model	
Stone et al. (2017)	Human capital Business process		Social media data Big data analytics
López-Robles et al. (2019)		Decision making	Big data
Yan et al. (2020)		Recommendations	Internet of things Big data

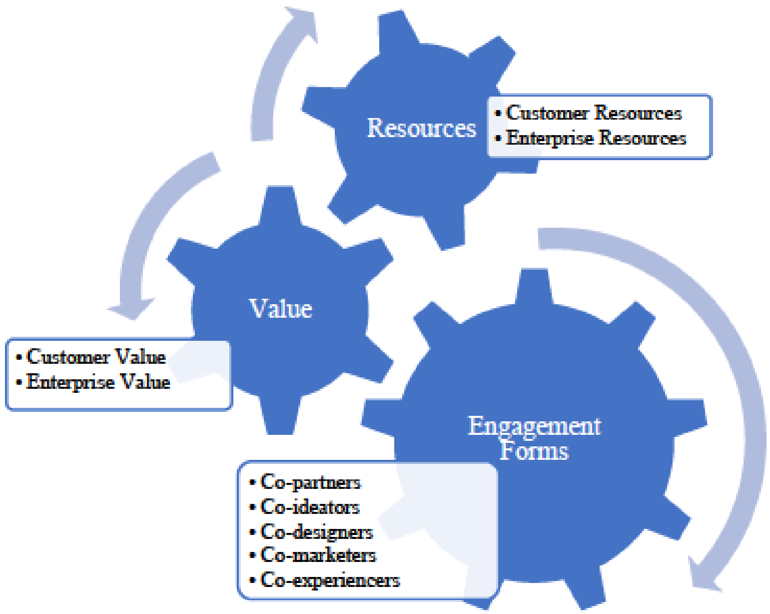
Source: Dam (2021)

Compared to other definitions of customer intelligence, the proposed definition seems to be more appropriate and complete, which considers all the three dimensions of the service science approach: science, management, and engineering (Maglio & Spohrer, 2013; Spohrer et al., 2007) The science dimension focuses on the process of creating, communicating, delivering, and co-creating offerings. The management dimension intensifies the values for customers. The engineering dimension demystifies knowledge and skills from big data and business analytics. The pre-eminence of the proposed definition is the emphasis on the value of co-creation with customers. The word "exchanging" in the original definition of marketing is replaced by the word "co-creating" to highlight the importance of customers with various roles in the age of big data. The final point to ponder is that the proposed definition of customer intelligence has accentuated the relevance of marketing decisions through the analytics of big data.

2.3.2 Characteristics of customer intelligence

This part touches upon the characteristics of co-creating customer intelligence for value as seen in Figure 2.5. Customer intelligence is co-created through the interactions of customers and enterprises. Value is a great motivation for customers and enterprises to participate in the co-creating process (Oertzen et al., 2018; Tu et al., 2018) whereas resources and engagement forms are significant means to facilitate customer intelligence (Laud & Karpen, 2017; Shamim et al., 2017).

Figure 2.5
Co-creating customer intelligence



Source: Dam (2021)

2.3.2.1 Co-creating customer intelligence for value

Value serves as a motivation that stimulates customer-enterprise and customer-customer interactions to co-create customer intelligence. As customers and enterprises are involved in this process, the thesis clarifies customer value and enterprise value.

Customer value relates to customers' motivational drivers in joining the co-creation process (Trischler et al., 2017). In other words, it describes the benefits that customers co-create with service providers (Cambra-Fierro et al., 2018). Customers' primary benefit when joining the co-creation process is to have their problem solved; therefore, their customer experience and satisfaction with the service are improved (Shamim et al., 2017; Vega-Vazquez et al., 2013). The value component clarifies what kinds of value are for customers and enterprises. Customers can also enjoy extrinsic values such as economic benefits including bonus points, monetary awards, discounts, or promotions by connecting new customers with service providers or even with partners of service providers (Fernandes & Remelhe, 2016; Rashid et al., 2019). Furthermore, customers can achieve social benefits by making friends with customers with common interests and exchanging experiences (Ranjan & Read, 2019; Zhang et al., 2015). The number of friends and followers on social media can infer the social status of customers (Quach & Thaichon, 2017; Verleye, 2015). Customers can learn from other customers, service providers, and also competitors; therefore, they receive knowledge benefits in the co-creation process (Xie et al., 2016). Benefits related to knowledge, peer recognition, friendship, or hedonic pleasure can be described as intrinsic values (OHern & Rindfleisch, 2010; Szirmai & Verspagen, 2015).

Enterprises receive economic value, innovation, competencies, and other desired outcomes from co-creating customer intelligence (Oertzen et al., 2018; Tu et al., 2018). The value that customer offers for enterprises can be categorized into three types: i) customer lifetime value (economic value), customer referral and influencer value (social value for influencing existing and potential customers), and customer knowledge value (cognitive value) (Oertzen et al., 2018; Xie et al., 2016). Knowledge and skills from customers are considered more significant as they are a great source for innovation and service improvement (Alves et al., 2016; Rashid et al., 2019).

2.3.2.2 Resources for co-creating customer intelligence

To co-create customer intelligence with customers, enterprises need to invest resources in this process (Storbacka et al., 2016; Xie et al., 2016). On the flip side, customers also possess resources that enterprises aim at exploiting for customer intelligence. (Im & Qu, 2017; Quach & Thaichon, 2017).

Customer resources can be individual resources including knowledge, skills, and experience relevant to service consumption (Im & Qu, 2017; Quach & Thaichon, 2017). Accordingly, the more knowledgeable customers are, the more likely they co-create (Im & Qu, 2017). Customer resources can also be the social network resources of customers (Iglesias et al., 2018; Martini et al., 2014). Through social media platforms, this resource reflects through network size (numbers of friends and followers) and their social roles (Fernandes & Remelhe, 2016; Laud & Karpen, 2017).

Enterprise resources include knowledge about the market and customers along with financial, human, and technological resources (Storbacka et al., 2016; Xie et al., 2016). Financial resources are incentives or monetary rewards that service providers offer to customers and employees to facilitate customer co-creation (Preikschas et al., 2017). In terms of human resources, previous studies give prominence to cross-functional teams and frontline employees to stimulate customer engagement in co-creating customer intelligence (Grönroos & Voima, 2013; Melton & Hartline, 2015). Direct and ongoing interactions between customers and service providers lead to more value (Grissemann & Sauer, 2012; Vega-Vazquez et al., 2013). Moreover, it is essential to take into consideration the participation style, team cohesion, and team identity of frontline employees along with task conflicts (Trischler et al., 2017; T. Zhang et al., 2018). Technological resources involve digital engagement platforms such as websites, social media, tools, and other interfaces (Frow et al., 2015; Verleye, 2015).

2.3.2.3 Engagement forms for co-creating customer intelligence

The engagement forms for co-creating customer intelligence discuss different mechanisms that incorporate customers and enterprises (Frow et al., 2015; Galvagno & Dalli, 2014). Among different roles, this thesis highlights the five roles of customers in co-creating customer intelligence that are mostly discussed in the literature: co-partners, co-ideators, co-designers, co-marketers, and co-experiencers (Dam et al., 2020; Iglesias et al., 2018; Tuan et al., 2019).

Customers can become co-partners by offering their knowledge and intelligence and receiving benefits from enterprises (Dam et al., 2020; Tuan et al., 2019). As customers develop skills and knowledge through experiencing products and services, their partnership yields positive outcomes for enterprises (Iglesias et al., 2018; Trischler et al., 2017). For example, customers of a customer relationship management (CRM) software can become experts, who can create and sell add-on apps for the user community (Libert et al., 2015). Therefore, other customers can enjoy additional services offered by other customers. Apple also sets a good example by providing customers with the iOS platform and software development kits to build and sell their applications (Storbacka et al., 2016). The diversity of apps on the Apple store enhances customer satisfaction. When customers can prove that they can offer value to enterprises as co-partners, they do not only receive profits but also have a chance to be recruited as experts or become business partners (Crandell, 2016; Frow et al., 2016).

As co-ideators, customers with product/service interests and passions often participate in the process of idea generation for the product/service conceptualization and improvement (Frow et al., 2016; Tuan et al., 2019). The interaction between an enterprise and customers facilitates the improvement of existing products/services and gradually stimulates ideas for product/service innovation (Crandell, 2016; Frow et al., 2016). In addition, customers can evaluate the ideas of others. For example, M&Ms customers can personalize their candies with different colors, text, and images (Libert et al., 2015). Starbucks launched the project called "My Starbucks Idea" allowing customers to express their ideas and discuss ideas with other customers (Russo-Spena & Mele, 2012).

At a higher level, customers can involve more as co-designers in product/service development (Frow et al., 2015; Ramaswamy & Ozcan, 2019). For the co-designing practice, customers are required to have a certain level of knowledge and skills related to product/service development (Rashid et al., 2019; Russo-Spena & Mele, 2012). To facilitate the customer co-designing process, enterprises often build engagement platforms, which can be a website, user design tool kits, virtual prototyping tools, or a joint process (Frow et al., 2015; Nambisan, 2010). Nikes exploits customers as co-designers by allowing them to design their running shoes through the website (Libert et al., 2015).

Customers can involve as co-marketers in participating in activities related to testing and sharing experiences about products/services (Frow et al., 2015). The primary goal of the co-marketing practice is to evaluate products/services and optimize customer experience (Russo-Spena & Mele, 2012). The co-marketing practice also encourages customers to share their user experiences (Božič & Dimovski, 2019). In fact, customers can discover new ways or shortcuts to consume a product/service; thus, product/service values can be leveraged (Melton & Hartline, 2015; Nambisan, 2010). Microsoft has created different online communities in which users share their experiences and support other users in solving their problems (Gibbert et al., 2002). From this co-creation approach, each Microsoft customer becomes a marketer through their participation in the online customer support service. No real marketer can outperform a customer as a co-marketer due to their experience with products/services and problems related to those products/services (Chen et al., 2018; Grissemann & Sauer, 2012).

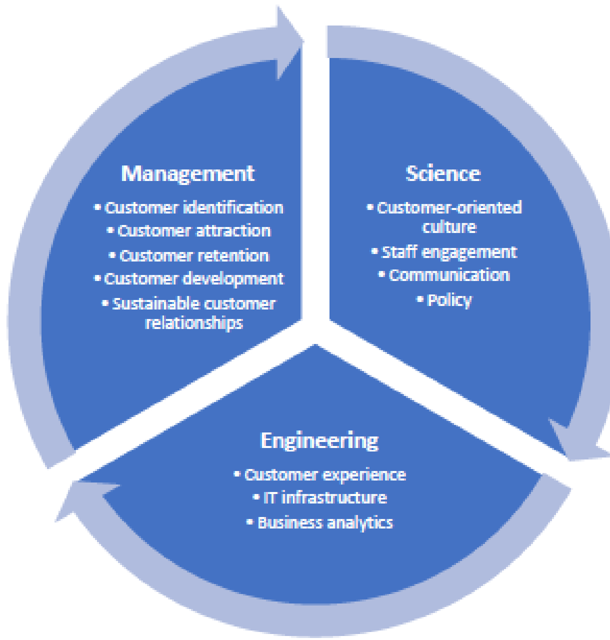
Customer co-experience aims at building the organizational structure and culture in which customers can experience as employees whereas employees can experience as customers (Leticia Santos-Vijande et al., 2013). From the customer-to-employee co-experience practice, customers have a chance to experience as real employees (Burrell, 2018; Melton & Hartline, 2015). In reality, Airbnb turns its customers into employees by providing an online database and services to support their customers to offer their housing for lease (Libert et al., 2015). Regarding the employee-to-customer co-experience practice, the first step to building a co-creation culture is to treat employees as customers by letting them complain about their job, their customers, and their colleagues (Quach & Thaichon, 2017; J. Z. Zhang et al., 2018). As mentioned above, if employees are not happy with the company, they cannot make their customers happy (Melton & Hartline, 2015; Yohn, 2018). Therefore, listening to employees' complaints will enhance the engagement and cohesiveness within an enterprise (Burrell, 2018;

Söderlund, 2020). It also aligns with each employee with a shared vision so that the value co-creation process can initially start among employees (Ramaswamy & Ozcan, 2018). Furthermore, employees should experience products/services as real customers. Putting employees in customers' shoes helps them better understand products/services and related issues (Melton & Hartline, 2015; Ranjan & Read, 2019). As a consequence, they are more likely to satisfy and co-create customer intelligence.

2.3.3 Customer intelligence for marketing benefits

As customer intelligence involves different aspects of enterprises to create marketing benefits, this section presents customer intelligence for marketing benefits from the three dimensions of management, science, and engineering of service science (O'Connor & Kelly, 2017; Pappas et al., 2018; Vargo & Lusch, 2017). As reflected in Figure 2.6, the management dimension focuses on the application of customer intelligence to offer marketing benefits for customers (Williams, 2018) whereas the science dimension strengthens the organizational viewpoint to facilitate the adoption of customer intelligence (Huang & Rust, 2021; Lim & Maglio, 2018; Saura et al., 2021). Finally, the engineering dimension discusses the role of technologies and analytics to transform big data into customer intelligence (Dam et al., 2021b; Sharma et al., 2019).

Figure 2.6
Marketing benefits from the service science approach



Source: Dam (2021)

2.3.3.1 From the management dimension

The management dimension aims at applying customer intelligence to offer marketing benefits (Williams, 2018). Various applications of customer intelligence are classified into the following main categories: customer identification, customer attraction, customer retention, customer development, and sustainable customer relationship (Ngai et al., 2009; Sigala, 2011; Siggelkow & Terwiesch, 2019).

In this spirit, customer intelligence is applied to identify customer segments with similar interests and profitability (France & Ghose, 2018; Ngai et al., 2009). Various demographic, psychographic, behavioral, or geographic criteria are used for customer segmentation (France & Ghose, 2019; Rygielski et al., 2002). Customer segmentation divides customers into homogenous segments and builds customer profiles (Amado et al., 2018; Fan et al., 2015). Customer profiles contain information on demography (age, gender), buying behaviors (needs, purchasing power, preferences, lifestyle), purchasing attributes (recency, frequency, size), product category, product mix, and estimated customer lifetime values (Baars & Kemper, 2008; France & Ghose, 2018). In this stage, enterprises can implement different data mining techniques related to target customer analysis to choose the most profitable segment (Davenport, 2006; Woo et al., 2005).

The objective of customer attraction is to attract customers through marketing strategies. Therefore, understanding customer behaviors is significant in responding to customer needs with relevant marketing strategies and tactics. The analysis of recency, frequency, and monetary of purchases can be applied to comprehend customer behavior and improve direct marketing strategy to attract customers (Hosseini et al., 2010). As a reflection of marketing strategies, pricing strategy and advertising campaigns are considered a great means to attract customers and improve business performance (Božič & Dimovski, 2019). Customer intelligence will help enterprises set optimal prices and decide whether to implement any price promotion to attract customers (Davenport et al., 2020). The application of customer intelligence can optimize the allocation of advertising costs. Once enterprises are capable of predicting customers' preferences, they can minimize advertising costs while still achieving profitable outcomes.

In order to retain a long-term relationship with customers, it is necessary to customize marketing strategies that suit customer preferences and behaviors (Amado et al., 2018; Payne & Frow, 2005). The key to increasing retention rates is to enhance and personalize service (Ngai et al., 2009; Zerbino et al., 2018). As a matter of fact, enterprises normally develop customer profiling, campaign management analysis, credit scoring, recommender systems, or loyalty programs to increase customer satisfaction and maintain long-term relationships (Payne & Frow, 2005; Rygielski et al., 2002).

With an aim to maximize value creation for enterprises, customer intelligence empowers service providers to identify potential opportunities from up/cross-selling, customer lifetime value, and market basket analysis (Ngai et al., 2009; Payne & Frow, 2005). While up-selling is the sales tactic that prompts customers to buy higher-priced or upgraded products, the cross-selling tactic is used for inducing customers to purchase related or complementary products (Seng & Chen, 2010; Zerbino et al., 2018). On the other hand, market basket analysis focuses on increasing the frequency and value of customer transactions through understanding their shopping habits and purchase trends (Baars & Kemper, 2008; Rygielski et al., 2002).

Sustainable customer relationship is defined as connected strategies in which enterprises are interconnected with customers 24/7 due to the application of technologies in the age of big data (Siggelkow & Terwiesch, 2019). Maintaining a continuous connection with customers helps enterprises improve service quality as well as customer experience (Siggelkow & Terwiesch, 2019; Trim & Lee, 2008). Instead of waiting for customers to come, enterprises applied customer intelligence by simulating customer experience to deal with customer concerns even before they arise in customers' heads (Anshari et al., 2019; Zerbino et al., 2018; J. Z. Zhang et al., 2018). With the support of customer intelligence, sustainable customer relationship is also developed through the application of customer lifetime values in allocating resources and investment in building relationships relevant to each stage of the customer lifetime (Zerbino et al., 2018; J. Z. Zhang et al., 2018).

2.3.3.2 From the science dimension

The science dimension focuses on the organizational viewpoint to support the adoption of customer intelligence in the business setting (Huang & Rust, 2021; Lim & Maglio, 2018; Saura et al., 2021). In this light, this part discusses the role of organizational structure/hierarchy, business process, business functions, people, and organizational culture to promote customer intelligence for marketing benefits (Fan et al., 2015; Gobble, 2015; Weinberg et al., 2013).

Customer-oriented culture is considered the most significant factor in the science dimension as it has such a significant impact on the business process, functions, people, leadership, and strategies (Yohn, 2018). Customer-oriented culture is defined as the beliefs and values of enterprises, which benefit customers (Tabrizi et al., 2019; Watkins, 2013). To instill a customer-oriented culture as a universal value, enterprises can start with leaders (Tabrizi et al., 2019), who need to establish a clear vision and leadership so that every employee is aware of their job responsibility and enterprise missions related to customers (Ramaswamy, 2009).

It is important to align leaders and employees with customer-oriented thinking, especially employees as they interact directly with customers (Tabrizi et al., 2019). Enterprises can consider hiring employees for customer orientation as a clear priority. Without a customer-oriented mindset, it is challenging for employees to understand customer needs, identify the motive behind their needs, and provide advantageous solutions (Gulati, 2010). It also poses threats to them in engaging with a customer-oriented enterprise (Burrell, 2018). In fact, employee engagement with enterprises stimulates positive customer outcomes. If employees are happy with enterprises, customers are more likely to be satisfied with such enterprises' services.

To promote a customer-oriented culture, enterprises should open up access for every employee to approach customer intelligence (Chen et al., 2021; Saura et al., 2021). Sharing customer intelligence across departments helps employees understand customers and get updated on customer experience (Yohn, 2018). Therefore, a flat hierarchy will facilitate the communication process as it eliminates the power distance among employees (Tabrizi et al., 2019).

In order to support the customer-oriented culture, enterprises should consider developing an appropriate incentive system (Rawson et al., 2013). It is important to take into account the discrepancy in the incentive policy between front-office and back-office employees (Gandomi & Haider, 2015; Samuel, 2015). As back-office employees are not rewarded for the number of ticket sales, they are more likely to process sales data with mistakes (Lemon & Verhoef, 2016; Rakthin et al., 2016).

2.3.3.3 From the engineering dimension

The engineering dimension discusses the role of technologies in acquiring, integrating, storing, and analyzing big data into customer intelligence (Dam et al., 2021b; Sharma et al., 2019). Accordingly, enterprises have to adapt to state-of-the-art data analytics and information technology (IT) infrastructures in the age of big data.

Customer experience also catches the attention of researchers and practitioners in the application of customer intelligence as it reflects the extent to which customers engage with products (Anshari et al., 2019; Hollebeek et al., 2019). Analyzing data to understand customer context is significant to manage customer experience and reinvent customer journeys from pre-purchases to post-purchases (Rawson et al., 2013; Tabrizi et al., 2019). Integrating and interpreting different sources of customer data help enterprises identify and prioritize key customer journeys; therefore, enterprises can improve customer experience and satisfaction (Söderlund, 2020; Tabrizi et al., 2019).

In terms of IT infrastructure, a repository supported by a data warehouse may be required to store customer data from different databases or servers to improve customer experience (Chen et al., 2012; Wamba et al., 2017). MySQL – an open-source relational database – is a popular choice for many enterprises to store customer data for executing SQL queries with low latency (Chaudhuri et al., 2011; Rao et al., 2018). In the age of big data, NoSQL or non-relational databases provides a great mechanism for handling extremely large data sets in volume, velocity, variety, and veracity (Chen et al., 2012;

Swami & Sahoo, 2018). Other database infrastructures may include intranets, open-source software (e.g.: Apache Hadoop, Pentaho, Zoho, Odoo, etc.), cloud-based platforms (Microsoft Azure, Amazon Web services, Google Cloud, etc.), or storage area networks (Chen et al., 2012; Davenport & Dyché, 2013; Wamba et al., 2017).

Analytic techniques that involve descriptive, predictive, and prescriptive are implemented to uncover information, knowledge, and intelligence behind data (Davenport & Dyché, 2013; LaValle et al., 2011). Descriptive analytics explains and learns from the past, whereas predictive analytics forecasts the future. Prescriptive analytics proposes the most optimal solutions for specific practical scenarios. Descriptive analytics is ideal to examine data from the past (Davenport & Dyché, 2013; Sivarajah et al., 2017). The most common techniques of descriptive analytics are business reporting, descriptive statistics, regression modeling, and visualization (Davis, 2014; Han et al., 2014; Sivarajah et al., 2017). As the characteristics of predictive analytics are to forecast future possibilities, it would make information more actionable (Janssen et al., 2017; LaValle et al., 2011; Van Auken, 2015). Predictive analytics relies on quantitative techniques such as statistic modeling, regression, and machine learning techniques to predict the future (Gandomi & Haider, 2015; García et al., 2017). With an aim to optimize business behaviors and actions, prescriptive analytics can be applied to convert knowledge into intelligence (Davenport & Dyché, 2013; Sivarajah et al., 2017). As recommendation-oriented analytics, prescriptive analytics is strongly believed to improve the efficiency of knowledge (Davenport & Dyché, 2013). Optimization and simulation are the most commonly used techniques to gain insights into complex business situations (Hu et al., 2014; Sivarajah et al., 2017).

2.4 RESEARCH GAPS

The literature review provides an overview of customer intelligence for marketing benefits and reveals research gaps. Among various research gaps on customer intelligence, the thesis focuses on three important areas which call for further research:

i) The ambiguity of customer intelligence; ii) The lack of mindset on management and organizational strategies; and iii) The Vague applications of customer intelligence marketing benefits. Each gap is also discussed with specific deficiencies in research and related literature as illustrated in Table 2.5.

Table 2.5
Research gaps

Research gaps	**Deficiencies in research**	**References**
The ambiguity of customer intelligence	- Confusion on different types of customer intelligence - The unclear analytic techniques to transform customer data into different types of customer intelligence	Crandell (2016); Fernandes and Remelhe (2016); France et al. (2015); Frow et al. (2016); Grönroos and Voima (2013); Heidenreich et al. (2015); Jouny-Rivier et al. (2017); OHern and Rindfleisch (2010).
Lack of mindset for management and organizational strategies	- Balancing the dimensions of management, organization, and technology in adopting customer intelligence.	Anshari et al. (2019); Chen and Popovich (2003); Cooke and Zubcsek (2017); Davenport and Spanyi (2019); Gibbert et al. (2002); Latinovic and Chatterjee (2019); Ngai et al. (2009).
Vague applications of customer intelligence for marketing benefits	- Applications of customer intelligence to offer marketing benefits remain unclear.	Cooke and Zubcsek (2017); Dam et al. (2022); Fotaki et al. (2014); Gobble (2015); Reijonen and Laukkanen (2010); Singh and Verma (2014).

Source: Dam (2021)

2.4.1 The ambiguity of customer intelligence

The ambiguity of customer intelligence lies in identifying types of customer intelligence corresponding with relevant analytic techniques.

The literature acknowledges the confusion on different types of customer intelligence (OHern & Rindfleisch, 2010; Ramaswamy & Ozcan, 2014; Ramaswamy & Ozcan, 2018). Due to the vast nature of this research stream, enterprises seem to lose track in identifying the right type of customer intelligence that fits their need (Chen et al., 2021; Dam et al., 2021b; Yan et al., 2020). It is challenging to define customer intelligence along with its relevant applications and data sources (Grönroos & Voima, 2013; Heidenreich et al., 2015; Laud & Karpen, 2017). It is argued that customer intelligence is advantageous; however, identifying the specific types of customer intelligence that match the business objectives is still an unresolved issue (Fernandes & Remelhe, 2016; Gustafsson et al., 2012). The clarification of specific types of customer intelligence along with data sources and business objectives should be further examined.

The reviewed literature indicates the urge to demystify the analytic techniques to transform customer data into customer intelligence (Branda et al., 2018; Burrell, 2018; Zerbino et al., 2018). Once enterprises determine the types of customer intelligence that fit their business objectives, it is necessary to identify corresponding data and analytic techniques (Verhoef & Lemon, 2013; Wedel & Kannan, 2016). In other words, enterprises, especially SMEs/SMOs, need to focus on the analytic techniques that match their needs, capabilities, and resources (Božič & Dimovski, 2019; Dam et al., 2022; Mikalef et al., 2019). Defining the right analytic techniques to explore the right data for the right type of customer intelligence is important in adopting customer intelligence (Fernandes & Remelhe, 2016; Lemon & Verhoef, 2016; Ngai et al., 2009).

2.4.2 The lack of mindset for management and organizational strategies

The lack of mindset for management and organizational strategies prompts the need to balance the dimensions of management, organization, and technology.

The literature provides various streams of research on the role of technology in handling extremely large customer data sets and mining customer intelligence (Chen et al., 2012; Swami & Sahoo, 2018). However, the mindset for the organizational and management strategies is not well-addressed. The organizational challenges involve managers' vision and organizational culture for stimulating customer intelligence (Song et al., 2018; Watkins, 2013). On the other hand, management challenges arise in business strategies and value creation from customer intelligence (Davenport & Spanyi, 2019; Erevelles et al., 2016; McGrath & McManus, 2020). Accordingly, the adoption of customer intelligence within enterprises should start with customers with relevant changes in management and organization instead of overwhelming in investing in technology (Davenport & Spanyi, 2019; Leeflang et al., 2014; Newman, 2018). In other words, it is significant to shift the focus on management along with adaptations to the organizational and technological dimensions.

2.4.3 Vague applications of customer intelligence for marketing benefits

This part presents the research gaps related to vague applications of customer intelligence for marketing decisions.

While the literature review points out many advantages of customer intelligence, the vague applications of customer intelligence for marketing decisions still emerge as a deficiency in research (Dam et al., 2022; Davenport & Spanyi, 2019; Yan et al., 2020). The application of specific types of customer intelligence for relevant marketing decisions is not a trivial task (Alves et al., 2016; Davenport et al., 2020). The value of customer intelligence is amplified and leveraged only if enterprises can make use of it for marketing decisions (Erevelles et al., 2016; Wedel & Kannan, 2016). These challenges prompt the motivation to study customer intelligence in the age of big data and develop the CIMB model to manage and leverage its value (Cooke & Zubcsek, 2017; Dam et al., 2021b; Gobble, 2015).

CHAPTER 3
A CONCEPTUAL MODEL

Based on the literature review in Chapter 2, Chapter 3 focuses on proposing a conceptual model of customer intelligence for marketing benefits (CIMB) and clarifying the research questions. Literature stimulates the need to clarify specific types of customer intelligence. Consequently, the objective of this chapter is to propose a conceptual model and to define the research questions with relevance to the particular types of customer intelligence and their applications to achieve marketing benefits. The chapter ends with the classification of the proposed research questions which sets the foundation for the research design.

3.1 CONSTRUCT DEVELOPMENT FROM THEORIES

Laid the foundation upon the literature review and theories in Chapter 2, the thesis continues by proposing a conceptual model of customer intelligence for marketing benefits. Based on the definition of a conceptual model, this section presents constructs of the proposed model which are developed from the four theories and reviewed articles.

A conceptual model is based on theories to develop factors, constructs, variables, and their relationships (Webster & Watson, 2002). In the other words, a conceptual model makes a logical sense of the relationships among constructs or variables (Okoli & Schabram, 2010). Furthermore, the conceptual model aims at synthesizing and extending existing studies to make theoretical contributions (Levy & Ellis, 2006). To set a solid foundation, conceptual models rely on theories and the literature to explain observed phenomena. Therefore, the conceptual model of customer intelligence for marketing benefits in this thesis is derived from the literature review in the previous part of this thesis and is based on the four theories, including the resource-based theory (Barney, 1991), the knowledge-based theory (Grant, 1996), the contingency theory

(Lawrence & Lorsch, 1967), and the service-dominant logic (Vargo & Lusch, 2004). These constructs, which are developed from these four theories and literature are explained in detail in the following part.

Table 3.1
Key Constructs of the CIMB Model

Key constructs	**Supported theories**	**Related works**
Customer intelligence	Resource-based theory (Barney, 1991); Knowledge-based theory (Grant, 1996).	Anshari et al. (2019); Chen and Popovich (2003); Davenport and Spanyi (2019); Gibbert et al. (2002); Gobble (2015); Lafrenière (2020); Latinovic and Chatterjee (2019); Rawson et al. (2013); Rygielski et al. (2002); Stone et al. (2017).
Customer data	Contingency theory (Lawrence & Lorsch, 1967); Resource-based theory (Barney, 1991).	Alves et al. (2016); Breidbach and Maglio (2016); Cambra-Fierro et al. (2018); Galvagno and Dalli (2014); Grönroos and Voima (2013); Heidenreich et al. (2015); Iglesias et al. (2018); Jouny-Rivier et al. (2017); Laud and Karpen (2017); OHern and Rindfleisch (2010); Prahalad and Ramaswamy (2004); Ramaswamy (2009); Ramaswamy and Ozcan (2016, 2019); Ranjan and Read (2019); Rashid et al. (2019).
Customer analytics	Knowledge-based theory (Grant, 1996).	Anshari et al. (2019); Baars and Kemper (2008); Božič and Dimovski (2019); Braganza et al. (2017); Davenport and Spanyi (2019).
Marketing benefits	Service-dominant logic (Vargo & Lusch, 2004).	Barile and Polese (2010); Beverungen et al. (2019); Lim and Maglio (2018); Medina-Borja (2015); Spohrer and Demirkan (2015).

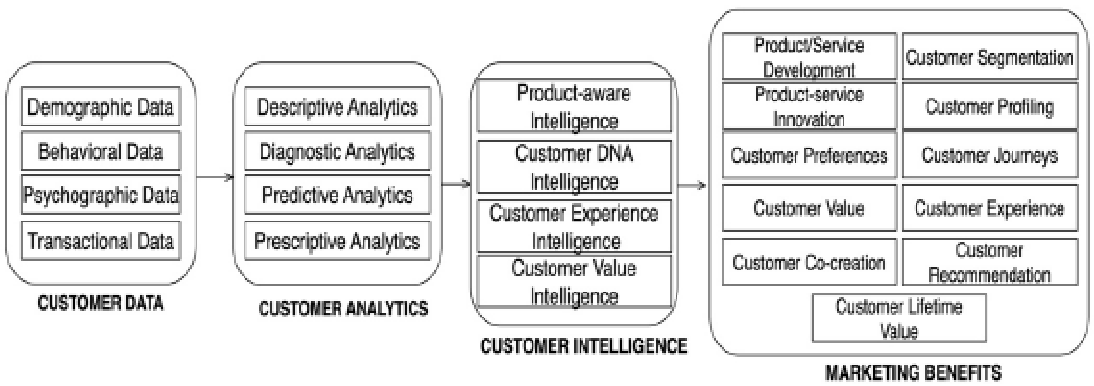
Source: Dam (2021)

The development upon the resource-based view (Barney, 1991), the knowledge-based view (Grant, 1996), the contingency theory (Lawrence & Lorsch, 1967), and the service-dominant logic (Vargo & Lusch, 2004) has identified and reinforced relevant constructs related to customer intelligence. A **construct** is defined as an abstract concept or a "phenomenon of interest" (Schryen, 2015; Webster & Watson, 2002). Accordingly, each theory infers various constructs associated with customer intelligence. The resource-based view (Barney, 1991) and the knowledge-based view (Grant, 1996) have indicated **customer intelligence** as a key construct. According to these theories, customer intelligence is considered a resource or knowledge within an enterprise. As a construct, customer intelligence might consist of sub-constructs such as data sources, competencies, or capability to generate customer intelligence (Gobble, 2015; Latinovic & Chatterjee, 2019; Zerbino et al., 2018). On the other hand, the contingency theory (Lawrence & Lorsch, 1967) gives prominence to external factors; therefore, it highlights the role of customers in generating data. The contingency theory (Lawrence & Lorsch, 1967) combined with the resource-based theory (Barney, 1991) nominate **customer data** as an important construct for customer intelligence. Besides, the knowledge-based view (Grant, 1996) emphasizes an enterprise as an institution for knowledge which emphasizes the role of **customer analytics** in transforming customer data into customer intelligence (Božič & Dimovski, 2019; Mikalef, Pappas, et al., 2020; Sahatiya, 2018). Finally, the service-dominant logic also infers **marketing benefits** as a significant construct related to customer intelligence (Heidenreich et al., 2015; Huang & Rust, 2018; Vargo & Lusch, 2008). Table 3.1 summarizes key constructs with supported theories and related work.

3.2 A CONCEPTUAL MODEL OF CUSTOMER INTELLIGENCE FOR MARKETING BENEFITS

Based on the literature view in Chapter 2, this section continues to present the conceptual model of customer intelligence for marketing benefits as demonstrated in Figure 3.1. The proposed model's contributions arise from further extending and clarifying constructs identified in the literature review. This section explains the service science approach in developing the proposed model and then explains the constructs including customer data, customer analytics, and customer intelligence. To emphasize the applications of different types of customer intelligence, specific marketing benefits for each type of intelligence are presented in the following section.

Figure 3.1
CIMB Model



Source: Dam (2021)

3.2.1 Service science approach

This section explains the motivations for applying the service science approach in developing the CIMB model. Subsequently, the advantages of the proposed model based on this approach are presented.

Considering the dominance of services and service-based products in the age of big data and the multidisciplinary nature of the study, this research relies on the service science approach which focuses on the configuration of management, science, and engineering to create value (Lusch et al., 2008; Spohrer et al., 2007). The service science approach is chosen to synthesize and extend constructs from the literature review in developing the model because it supports current Marketing Science with a focus on marketing benefits (Erevelles et al., 2016; Huang & Rust, 2021; Lies, 2019).

Under the lens of the service science approach, the CIMB model involves the economic exchange process in which people interact, learn, and adapt to benefit each other. With the focus on economic exchange, the service science approach is in line with marketing science (Spohrer et al., 2007) and service-dominant logic (Vargo & Lusch, 2008). Marketing science has witnessed the shift from goods production to service provision in the modern economy. Finally, developing the CIMB model based on the service science approach also fits the objectives of the thesis.

Laid the groundwork upon the four theories and the service science approach (Maglio & Spohrer, 2013; Spohrer et al., 2007), the CIMB model is proposed with reflections on the science, management, and engineering dimensions. The science dimension focuses on the organizational viewpoint whereas the management dimension covers the strategic viewpoint. The engineering dimension touches upon the technological viewpoint. Through this approach, customer intelligence can make a fundamental shift to the core service value of enterprises, particularly the science dimension. In the proposed model, the engineering dimension focuses on acquiring customer data from diverse sources including websites, media social, internal systems of enterprises, and other open sources. The science dimension aims at applying customer analytics to transform customer data into customer intelligence. Finally, the management dimension aims at creating marketing benefits from customer intelligence.

3.2.2 Customer data

Customers create a significant amount of data, which is also known as big data, through interactions with enterprises and other customers on different online platforms (Fan et al., 2015). As illustrated in Table 3.2, this study classifies customer data into four types (Huang & Rust, 2021; Liang & Liu, 2018; Lies, 2019; Saura et al., 2021): *i)* Demographic data – Who customers are, *ii)* Behavioral data – How customers interact?, *iii)* Psychographic data – Why customers buy?, and *iv)* Transactional data – What customers buy?. Specific types and sources of customer data are also elucidated as follows.

Table 3.2
Classification of customer data

Data types	**Demographic data**	**Behavioral data**	**Psychographic data**	**Transactional data**
Functions	***Who*** are customers?	***How*** do customers interact?	***Why*** do customers buy?	***What*** do customers buy?
Specific types	Age, gender, profession, location, income, and marital status.	Clickstream data, add-to-favorites, add-to-cart, likes, shares, comments.	Lifestyles, interests, preferences, and habits.	Historical purchases, invoices, payment.
Sources	Census Bureau, StatsCan, social media, CRM systems.	Websites, social media, mobile devices.	Websites, social media, Surveys, CRM systems.	Transaction records, sales reports, billing records, CRM systems.

Source: Dam (2021)

Demographic data reveal ***Who*** customers are (France & Ghose, 2018). Demographic data contain data on age, gender, profession, location, income, and marital status segmentation (Erevelles et al., 2016; France & Ghose, 2018). Customer segmentation relies on demographic data to define the target audience. For instance, the U.S Census Bureau and StatsCan are the primary sources of demographic data. Nowadays, social media such as Facebook, and Twitter can provide demographics (Holmlund et al., 2020). For example, customers checking in on social media can provide location-based data (Fan et al., 2015).

Behavioral data show ***How*** customers interact with enterprises and products (Hosseini et al., 2010; Rawson et al., 2013). Social media, websites, and mobile devices provide a significant amount of behavioral data (Amado et al., 2018). Customer interactions on websites and mobile devices - particularly clickstream data, add-to-favorites, and add-to-cart data can reveal customer behaviors (Chen et al., 2012; Fan et al., 2015). On the other hand, customers' likes, shares, and comments on social media become a great source to gain customer opinions as these digital platforms offer real-time updates on customers' behaviors (France & Ghose, 2018; Ngai et al., 2009).

Psychographic data explain ***Why*** customers buy products (Holmlund et al., 2020; Lafrenière, 2020). Psychographic data involve translating demographic, behavioral, and transactional data to reveal the lifestyles, preferences, and habits of customers (Hong & Kim, 2012). Similar to other data, data sources for psychographic data are websites, social media, surveys, and CRM systems (Chen et al., 2012; Fan et al., 2015). In the age of digitalization, text mining on social media is often applied to derive psychographic data (Amado et al., 2018).

Transactional data unveil ***What*** customers buy (Anshari et al., 2019; Holmlund et al., 2020). Various types of transaction data are historical purchases, invoices, and payments (Erevelles et al., 2016; Fan et al., 2015). Transactional data can be found from various sources such as transaction records, sales reports, billing records, and CRM systems (Chen et al., 2012; Sivarajah et al., 2017). The integration of transactional data from various sources is important as the reflection of historical purchase data shows how customers value products/services(Hosseini et al., 2010; Rygielski et al., 2002).

3.2.3 Customer analytics

Before various analytic techniques can be applied to analyze and interpret data, it is important to prepare data as the nature of real-world data is incomplete, inaccurate, and inconsistent (Hu et al., 2014; Sivarajah et al., 2017). Once data preparation is completed, descriptive, diagnostic, predictive, and prescriptive analytics are implemented to uncover customer intelligence (Chen et al., 2012; Sivarajah et al., 2017). Detailed descriptions of these analytics are presented as follows.

Descriptive analytics is ideal to explore historical data and transform them into information. Descriptive analytics techniques refer to business reporting, descriptive statistics, regression modeling, and visualization (Wedel & Kannan, 2016). Business reporting involves the process of generating standard reports, ad hoc reports, query/drill down, and alerts (Chen et al., 2012; Sivarajah et al., 2017). Different descriptive statistical methods such as association, clustering, regression, decision trees, etc. are applied to analyze business reports. Regression is the most widely used analytic technique to find out trends in customers from historical data (Hu et al., 2014; Sivarajah et al., 2017). Visual presentation of customer data is frequently used to better communicate the results of descriptive analytics (Rao et al., 2018).

Based on descriptive analytics outcomes, diagnostic analytics responds to the question "why did it happen?" with techniques such as data mining, data discovery, and correlations (Lu et al., 2020; Sivarajah et al., 2017). To put it another way, diagnostic analytics explains why something happened in the past by examining the root of the problems (Akter & Wamba, 2019). Enterprises can rely on insight from diagnostic analytics to examine relationships among variables and test hypotheses. A wide range of analysis techniques falls in diagnostics analytics such as conjoint analysis, sensitive analysis, and trend analysis (Wedel & Kannan, 2016).

As the characteristic of predictive analytics is to forecast future possibilities, it would make information more actionable (Sivarajah et al., 2017). Predictive analytics relies on quantitative techniques such as statistic modeling, regression, and machine learning techniques to predict the future (Erevelles et al., 2016; Wedel & Kannan, 2016). Accordingly, linear regression techniques and statistic modeling are conducted to explore interdependencies among variables and make predictions concerning customer behaviors and preferences (Davenport & Dyché, 2013; Sivarajah et al., 2017). Different machine learning techniques such as neural network algorithms, and self-organizing maps provide insights and future outcomes for customers (Hu et al., 2014; Sivarajah et al., 2017).

With an aim to optimize business behaviors and actions, prescriptive analytics can be applied to convert customer insights into customer intelligence (Davenport & Dyché, 2013; Sivarajah et al., 2017). As recommendation-oriented analytics, prescriptive analytics is strongly believed to improve the efficiency of customer insights (Davenport & Dyché, 2013). Regarding prescriptive analytics, optimization and simulation are the most commonly used techniques to gain insights into customers for complex business situations (Hu et al., 2014; Sivarajah et al., 2017). While simulation contributes to the handling of complex problems, optimization proposes the most optimal solution considering certain constraints.

3.2.4 Specific types of customer intelligence

Based on different types of customer data, customer intelligence is classified as product-aware intelligence, customer DNA intelligence, customer experience intelligence, and customer value intelligence. These specific types of customer intelligence are proposed based on the 4Cs marketing model (Lauterborn, 1990) including consumer wants and needs, convenience, communication, and cost. The subsection clarifies the development of these four types of customer intelligence based on the 4Cs marketing model corresponding with customer data.

Product-aware intelligence clarifies the first C of "consumer wants and needs" (Lauterborn, 1990). Product-aware intelligence demystifies *what* customers like and develops products/services based on their needs (Wedel & Kannan, 2016; Zuberi & Rajaratnam, 2020). Product-aware intelligence contains customer insights and preferences on products/services by mining customer opinions through customer reviews, discussions, behaviors on forums, social media, blogs, and websites (Quach

& Thaichon, 2017; Ramaswamy & Ozcan, 2018). Acquiring user-generated content and web content allows enterprises to develop product/service solutions to deliver value for customers (Saura et al., 2017; Xie et al., 2016). Being aware that enterprises are under the pressure of innovation in the service-based era, production-aware intelligence emerges as an optimal solution for such a challenge. Accordingly, product-aware intelligence deals with product/service innovation in optimizing product/service features and characteristics along with providing a unique and remarkable experience that offers value for customers (Gobble, 2015; Roberts et al., 2016).

In favor of communicating with customers, enterprises can improve the second C – communication – by gaining insights into customer sentiment, preferences, and satisfaction (Lauterborn, 1990). Customer DNA intelligence aims at identifying, targeting, and positioning customers for personalized services (Davenport & Spanyi, 2019; Hollebeek et al., 2019). Based on customer DNA intelligence, enterprises can divide a business market into sub-groups of customers with similar characteristics and develop into customer profiles (Amado et al., 2018; Fan et al., 2015). Customer profiles provide the breakdown of demographic information such as age, gender, marital status, household income, and occupation (Lu et al., 2020; Yan et al., 2020). Therefore, enterprises can find and target the most attractive segment. In other words, customer DNA intelligence supports the Segmentation, Targeting, and Positioning (STP) process so that enterprises can better communicate and personalize messages to customers (Anshari et al., 2019; Rygielski et al., 2002; Yan et al., 2020).

Customer experience intelligence refers to *How* customers interact with enterprises and products (Holmlund et al., 2020; Ramaswamy & Ozcan, 2019). To facilitate customer interaction, the third C – convenience – is supported with customer experience intelligence in optimizing customer services (Lauterborn, 1990). Customer experience intelligence empowers enterprises to provide better services by understanding journeys, behaviors, engagement, and co-creation of customers. Analyzing activity data of customers is significant to manage customer experience and reinvent *customer journeys* from pre-purchases to post-purchases for better service creation (Rawson et al., 2013; Tabrizi et al., 2019). Customer experience intelligence also demystifies value, resources, and engagement forms to facilitate *customer co-creation* (Alves et al., 2016; Ramaswamy & Ozcan, 2019). Understanding these mechanisms of customer co-creation reveals customer motivations and reasons for the consumption of products and services. Consequently, enterprises can count on customer experience intelligence to understand customer sentiment, improve customer satisfaction, and boost customer loyalty (Erevelles et al., 2016; Xie et al., 2016).

Customer value intelligence unveils *What* the value of customers is (Anshari et al., 2019; Holmlund et al., 2020). Customer value intelligence determines the last C – cost – in estimating the value of customers which drives marketing strategies (Lauterborn, 1990). Customer value intelligence works toward maximizing customer value for enterprises. Literature categorizes customer value into economic, social, and cognitive value (Oertzen et al., 2018; Xie et al., 2016). Economic value aims at making the most profits from customers by measuring customer lifetime value whereas social value takes advantage of their social influence from networks on social media through the reflection of customer influencer value. Lastly, cognitive value aspires to the knowledge and experience of customers for co-creation value. With the support of customer lifetime value intelligence, enterprises can predict the total monetary value that customers are expected to spend for an enterprise during their lifetime (Ngai et al., 2009). On the other hand, customer influencer value intelligence avails customers of their social status and networks to spread word of mouth (WOM) to influence others (Quach & Thaichon, 2017; Verleye, 2015). Finally, customer co-creation value makes sense of relevant value, resources, and engagement forms to encourage them to co-create value.

3.3 THE APPLICATIONS OF CUSTOMER INTELLIGENCE FOR MARKETING BENEFITS

This part continues with the applications of customer intelligence for marketing benefits. In this light, marketing benefits for each type of customer intelligence are discussed in detail. Figure 3.2 presents the data mining methods and algorithms relevant to specific marketing benefits of customer intelligence. There are six typical data mining methods that extract customer intelligence for various applications as follows (Davenport & Dyché, 2013; Gandomi & Haider, 2015; Ngai et al., 2009):

- The classification method determines and predicts attributes of clusters such as customers or products (France & Ghose, 2018; Holmlund et al., 2020). Examples of classification techniques are neural networks, decision trees, random forest classification, and support vector machines.

- The association method figures out the correlations between products-products, customers-customers, and products-customers (Ngai et al., 2009; Yan et al., 2020). Association techniques include apriori, graph-based matching, market basket analysis, and association rules.

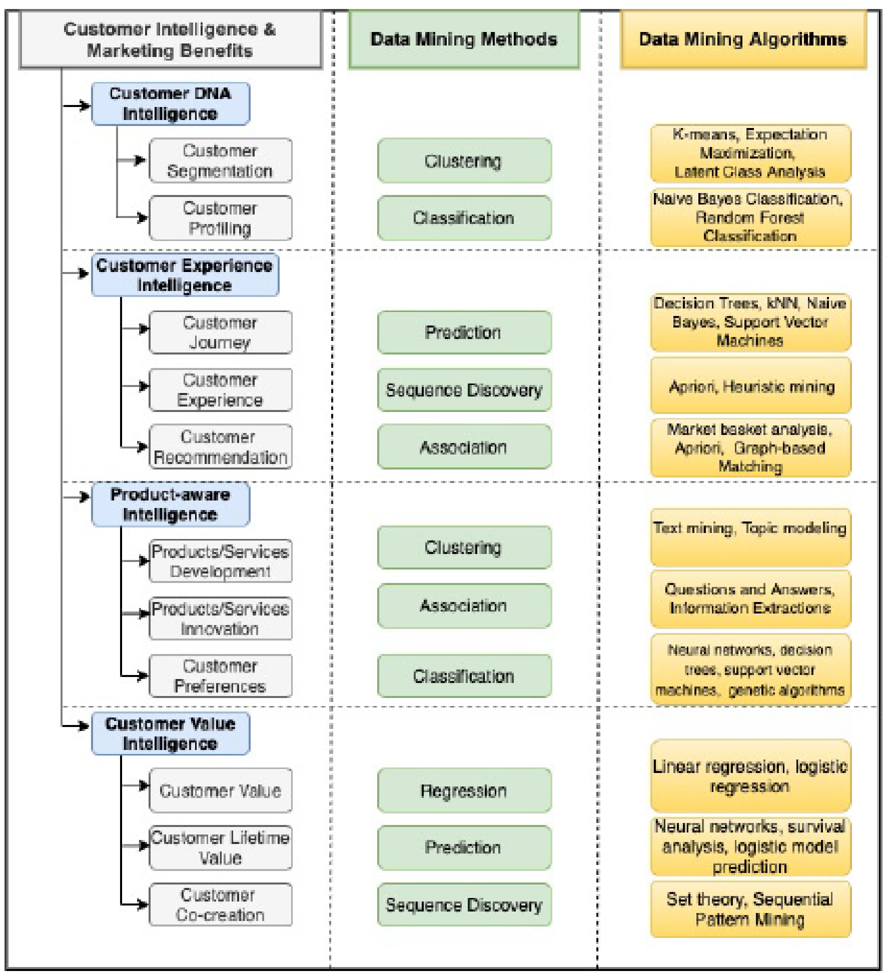
- The clustering method divides a population into homogenous subgroups with similar characteristics (Rygielski et al., 2002; Yan et al., 2020). In clustering, different techniques can be found are K-means, the Naïve Bayes technique, neural networks, and self-organizing map techniques.

- The regression method explains and predicts causal relationships among variables (Dam et al., 2019; Wu et al., 2013). The most often used regression techniques are linear regression and logistic regression.

- The prediction method estimates and foresees future behaviors and value based on historical records (Chen et al., 2012; Davenport & Dyché, 2013). Typical prediction methods are logistic model prediction, neural networks, and survival analysis

- The sequence discovery method identifies hidden patterns and describes orders of behaviors in sequential data (Wu et al., 2013; Yan et al., 2020). Common sequence discovery techniques are set theory and sequential pattern mining.

Figure 3.2
Marketing benefits associated with analytic techniques



Source: Dam (2021)

3.3.1 Product-aware intelligence for marketing benefits

Product-aware intelligence is applied to elucidate what to offer to customers to satisfy their needs. Products and services are considered solutions to deliver value for customers (Fan et al., 2015). Therefore, enterprises are under pressure for the development and innovation of products and services (Burrell, 2018; Frow et al., 2015).

Customer product/service development relies on clustering, particularly text mining and topic modeling to examine customers' needs and expectations for new products/services (Anshari et al., 2019; Zerbino et al., 2018). The application of customer intelligence in service and product development would yield profitable outcomes (Davenport & Spanyi, 2019; Erevelles et al., 2016). It keeps track of changes in markets and customer preferences as it is extracted from customer interactions on digital platforms (Rakthin et al., 2016; Verleye, 2015). Nowadays, customers increasingly express their voices on social media, which creates a significant amount of real-time user-generated data for product development and customer services (Fan et al., 2015; Singh & Verma, 2014).

Customer product/service innovation counts on information extraction, questions and answers of the association method to make changes to existing products/services (Burrell, 2018; Frow et al., 2015). Customers can involve as co-ideators for product/service innovation (Burrell, 2018; Frow et al., 2015). In fact, customers with product/service interests and passions often participate in the process of idea generation for the product/service conceptualization and improvement (Oertzen et al., 2018; Rashid et al., 2019). The interaction between an enterprise and customers facilitates the improvement of existing products/services and gradually stimulates ideas for product/service innovation.

Customer preferences result from the deployment of classification techniques such as neural networks, decision trees, support vector machines, and generic algorithms.

Product-aware intelligence measures the overall emotion of customers towards products/services and verifies if products/services can meet customer expectations (Holmlund et al., 2020; Wedel & Kannan, 2016). Understanding customer preferences is significant in responding to customer needs and developing promotional strategies and tactics (Anshari et al., 2019; Zerbino et al., 2018).

3.3.2 Customer DNA intelligence for marketing benefits

Customer DNA intelligence identifies who customers are. Therefore, this type of intelligence can support enterprises with customer segmentation and customer profiling (France & Ghose, 2018; Holmlund et al., 2020).

Customer segmentation reckons on K-means, latent class analysis, expectation maximization of the clustering method to divide customers into homogenous segments and builds customer profiles (Amado et al., 2018; Fan et al., 2015). Customer identification focuses on how to identify the most profitable customers (Amado et al., 2018; Fan et al., 2015). In fact, it is challenging to identify the most lucrative customer segments due to the huge volume and variety of big data. Customer intelligence is applied to identify customer segments with similar interests and profitability (France & Ghose, 2018; Ngai et al., 2009). Various demographic, psychographic, behavioral, or geographic criteria are used for segmentation (France & Ghose, 2018; Rygielski et al., 2002).

Customer profiling applies different classification techniques such as the Naïve Bayes technique, random forest classification to develop customer profiles (France & Ghose, 2018; Holmlund et al., 2020). Customer profiles contain information on demography, buying behaviors, purchasing attributes, product category, and estimated customer lifetime value (France & Ghose, 2018; Holmlund et al., 2020). Due to customer intelligence, enterprises can implement different data mining techniques related to target customer analysis to choose the most profitable segment (Fan et al., 2015; Ngai et al., 2009). Enterprises rely on customer profiling to develop marketing campaigns and maintain long-term relationships with customers (Davenport & Spanyi, 2019; Lemon & Verhoef, 2016).

3.3.3 Customer experience intelligence for marketing benefits

Customer experience intelligence clarifies customer journeys from pre-purchase to post-purchase. Furthermore, customer experience intelligence elucidates customer experience in each journey to facilitate customer co-creation.

Customer journeys highlight the importance of the prediction method to design and optimize customer journeys (Siggelkow & Terwiesch, 2019). Accordingly, service providers attempt to map customer journeys with key touchpoints in each stage through the application of different mining techniques including decision trees, kNN, Naïve Bayes, support vector machines (Halvorsrud et al., 2016; Maechler et al., 2016). Customer intelligence can be applied to design and optimize customer journeys by understanding customer needs, suggesting products or services that might meet their needs, and following up the delivery of service and products (Siggelkow & Terwiesch, 2019). In other words, the three stages represent the pre-purchase, purchase, and post-purchase of a customer journey (Rawson et al., 2013). Accordingly, service providers attempt to map customer journeys with key touchpoints in each stage (Halvorsrud et al., 2016; Maechler et al., 2016).

Customer experience takes advantage of the sequence discovery method (e.g., apriori, heuristic mining) to improve their satisfaction in interacting with the website of an enterprise. It catches the attention of researchers and practitioners as it reflects the extent customers engage with products (Burrell, 2018; Holmlund et al., 2020). Customer intelligence is capable of enhancing personalized customer experience through analytics and excavation of big data (Yan et al., 2020). In particular, analyzing customer-generated contextual data is significant to manage customer experience and to reinvent customer journeys from pre-purchases to post-purchases (Lemon & Verhoef, 2016; Rawson et al., 2013). Furthermore, integrating and interpreting different sources of customer data help enterprises identify and prioritize key customer journeys to optimize customer experience (Tabrizi et al., 2019).

Customer recommendation significantly puts trust in the association method through the reflection of different techniques such as market basket analysis, apriori, graph-based matching to figure out the interrelationships between products and users (Dam & Le Dinh, 2020; Yan et al., 2020). The application of customer intelligence in recommender systems promotes the optimization of customer experience from finding to engaging with products/services (Lies, 2019; Sharma et al., 2019). Recommender systems take advantage of data related to products and customers to predict and recommend the most relevant services or products. It is noted that customer intelligence is applied as an important part of the development of recommender systems (Dam & Le Dinh, 2020; Yan et al., 2020).

3.3.4 Customer value intelligence for marketing benefits

Customer value intelligence identifies and calculates different types of value that customers can offer. Executives can rely on customer value intelligence to choose the most valuable customers and to maximize value creation from them.

Customer values bank on various regression techniques such as linear regression, logistic regression to bring values for enterprises (Ngai et al., 2009; Yan et al., 2020). Customers can offer value for enterprises. Customer value can be categorized into three types: i) Economic value – the measure of profits), ii) Social value – how customers influence other customers, and iii) Cognitive value – value gained from customers' knowledge and experience (Oertzen et al., 2018; Verleye, 2015). In the era of big data, knowledge and skills from customers are considered more significant as they are a great source of customer intelligence.

Customer lifetime value gives prominence to the prediction method to forecast the total monetary value that customers are expected to spend for an enterprise during their lifetime (Ngai et al., 2009). It is a prediction of the total monetary value that customers are expected to spend for an enterprise during their lifetime (Ngai et al., 2009). With the support of customer intelligence, service providers will have sufficient data and information to estimate customer lifetime value (Ngai et al., 2009; Yan et al., 2020). Therefore, they can fine-tune their marketing strategies, particularly strategies related to segmentation, targeting, and positioning, for optimal outcomes (Anshari et al., 2019; Rygielski et al., 2002; Yan et al., 2020).

Customer co-creation turns to the sequence discovery method (e.g., set theory, sequential pattern mining) to offer relevant resources, value, mechanisms to stimulate customers to interact with enterprises to create values from their knowledge and experiences. Customer co-creation is described as the joint creation of value by the service providers and customers through the mutual application of operant resources (Oertzen et al., 2018; Rashid et al., 2019). From the standpoint of service providers, customer value co-creation provides a significant source of customer data for product and service innovation (Dam & Le Dinh, 2020; Yan et al., 2020). From the perspective of customers, customer value co-creation improves customer experiences and knowledge (Ramaswamy & Ozcan, 2019).

3.4 RESEARCH OBJECTIVE AND RESEARCH QUESTIONS

Based on the CIMB model, this section summarizes and finalizes the research objectives along with relevant research questions.

Considering the challenges and opportunities of big data, SMEs/SMOs in the cultural sector are under pressure for value creation in marketing to survive and prosper in the age of big data. As presented in the previous section, most enterprises are not clear on the notion of customer intelligence in the context of big data as it lies at the junction of big data and customer knowledge (Davenport & Spanyi, 2019; Tabrizi et al., 2019). It is noted that enterprises are obsessed to take advantage of customer intelligence; nevertheless, they lose track in defining and applying customer intelligence to create value for marketing benefits (Davenport & Spanyi, 2019; Lies, 2019). Consequently, the research objective is to develop a customer intelligence model to achieve marketing benefits in the age of big data, particularly for cultural SMEs/SMOs. Based on the general objectives, there are two specific objectives. The primary specific objective of the thesis is to clarify the specific types of customer intelligence along with data types and analytic techniques for customer intelligence. The secondary specific objective is to apply customer intelligence for marketing benefits, particularly for SMEs/SMOs in the cultural sector. Table 3.3 summarizes the breakdown of these research objectives.

Table 3.3
Research Objectives

Objectives	**Descriptions**
Objective 1	Identification of Customer intelligence
1.1	Identifying specific types of customer intelligence
1.2	Identifying specific types of customer data
1.3	Identifying specific types of analytic techniques for each type of customer intelligence
Objective 2	Applications of Customer intelligence for Marketing Benefits
2.1	Clarifying marketing benefits corresponding with different types of customer intelligence
2.2	Leveraging marketing benefits from customer intelligence

Source: Dam (2021)

To respond to the research objective, the following research questions (RQ) with specific questions are explored. The first research question involves the identification of customer intelligence whereas the second research question concerns the applications of customer intelligence for marketing benefits. To validate these research questions and prepare for the research methodology, the next part of the thesis presents rules of research questions to guide the research design.

RQ 1: How to transform customer data into customer intelligence in the age of big data considering the context of SMEs/SMOs in the cultural sector?

RQ 1.1: *What are relevant types of customer intelligence?*

RQ 1.2: *What are analytic techniques to transform customer data into customer intelligence?*

RQ 2: How to apply customer intelligence to achieve marketing benefits in the context of SMEs/SMOs in the cultural sector?

RQ 2.1: *What types of marketing benefits correspond with customer intelligence?*

RQ. 2.2: *How to leverage marketing benefits from customer intelligence?*

3.5 RULES AND CLASSIFICATION FOR ANALYZING RESEARCH QUESTIONS

With an aim to investigate the proposed research questions, this section continues to examine the types, functionalities, characteristics, and typology of research questions. Accordingly, the proposed research questions are analyzed in detail. The classification of proposed research questions set out the foundation for the research design which is presented in the next chapter of the thesis.

Research questions play a significant role as they are in charge of guiding research design and research methods (Bryman, 2007). Based on these research questions, the methodological position and research design are tailored to guide an investigation. Research questions are considered a focal point of social research which can provide the key to planning and carrying out a successful research project. Certain types of research questions are relevant to the quantitative approach whereas others follow a qualitative one (Thornhill et al., 2009). In some cases, research questions call for both qualitative and quantitative data collection methods (Palys & Atchison, 2012; Patton, 1990). For example, one research question for the quantitative approach and the other question for the qualitative approach.

Research questions have four key functionalities: i) define the project, ii) set boundaries, iii) give directions, and iv) define success (O'leary, 2004). Firstly, research questions can define the project and summarize what the research topic is involved in. Secondly, research questions set boundaries for the research focus. Thirdly, the research questions give direction in searching the literature, data collection, and analysis method. Lastly, research questions define success by confirming the credibility of research results.

Table 3.4
Classification of Research Questions

Types of research methods	**Type of research questions (RQ)**	**Typology**	**Purposes**
Qualitative research	Exploratory RQ	What, How	Learn about a topic.
	Predictive RQ	Yes/No	Predict future outcomes.
	Interpretive RQ	How, What	Explain a phenomenon.
Quantitative research	Descriptive RQ	What, How	Explain when, where, why, or how a phenomenon occurred.
	Comparative RQ	Why	Compare relationships
	Causal RQ	How	Examine cause and effect.

Source: Robson and McCartan (2016) and Thornhill et al. (2009)

With an aim to improve research quality, this thesis also takes a closer look at the characteristics of good research (Robson & McCartan, 2016). Accordingly, good research questions should be clear and able to demonstrate research purposes. Other characteristics of good research questions are significant and answerable (Patton, 1990; Thornhill et al., 2009). As such, researchers should be able to collect relevant data to respond to research questions. Finally, good research questions can form a coherent interconnected set.

There are types of research questions: What, Why, and How. "What" questions describe characteristics of research objects whereas "why" questions focus on explanation and understanding (Thornhill et al., 2009). Lastly, "how" questions involve changes in research objects. Qualitative research categorizes into three types: exploratory, predictive, and interpretive (Onwuegbuzie & Leech, 2007; Patton, 1990). Exploratory research questions which formulate "what" and "how" questions aim at learning about a topic. Predictive questions deal with the future outcome of an action. Interpretive questions explain a phenomenon. On the flip side, quantitative research consists of descriptive, comparative, and causal questions (Robson & McCartan, 2016). Descriptive questions explain when, where, why, or how a phenomenon occurred. Comparative questions look at the relationships between two or more variables. Causal questions examine how a variable can influence another.

Based on the classification of research questions in Table 3.4, the research questions proposed in the thesis are also examined. As illustrated in Table 3.5 the purpose of the first proposed research question (RQ 1) is to learn about specific types of customer intelligence in the era of big data in the context of SMEs/SMOs in the cultural sector. RQ 1 is formulated with the *How* typology. The purpose along with the typology reveals that RQ 1 is an exploratory question that corresponds with the qualitative research. Similarly, the purpose of the second research question (RQ 2) is to learn about the applications of customer intelligence for marketing benefits in the context of SMEs/SMOs in the cultural sector. RQ 2 is also framed by the *How* typology.

Consequently, RQ 2 is categorized as an exploratory question. Literature suggests that qualitative research would best suit exploratory questions (Robson & McCartan, 2016). The classification of proposed research questions set out the foundation for the research design. Chapter 4 continues with the methodological position and approach to respond to the research questions.

Table 3.5
Classification of the proposed research questions

Research Questions (RQ)	**Purposes**	**Typology**	**Types of RQ**	**Types of methods**
RQ 1: How to transform customer data into customer intelligence in the age of big data considering the context of SMEs/SMOs in the cultural sector?	To learn about customer intelligence in the context of SMEs/SMOs in the cultural sector.	How	Exploratory	Qualitative
RQ 2: How to apply customer intelligence to achieve marketing benefits in the context of SMEs/SMOs in the cultural sector?	To learn about the applications of customer intelligence for marketing benefits in the context of SMEs/SMOs in the cultural sector.	How	Exploratory	Qualitative

Source: Dam (2021)

CHAPTER 4
RESEARCH DESIGN

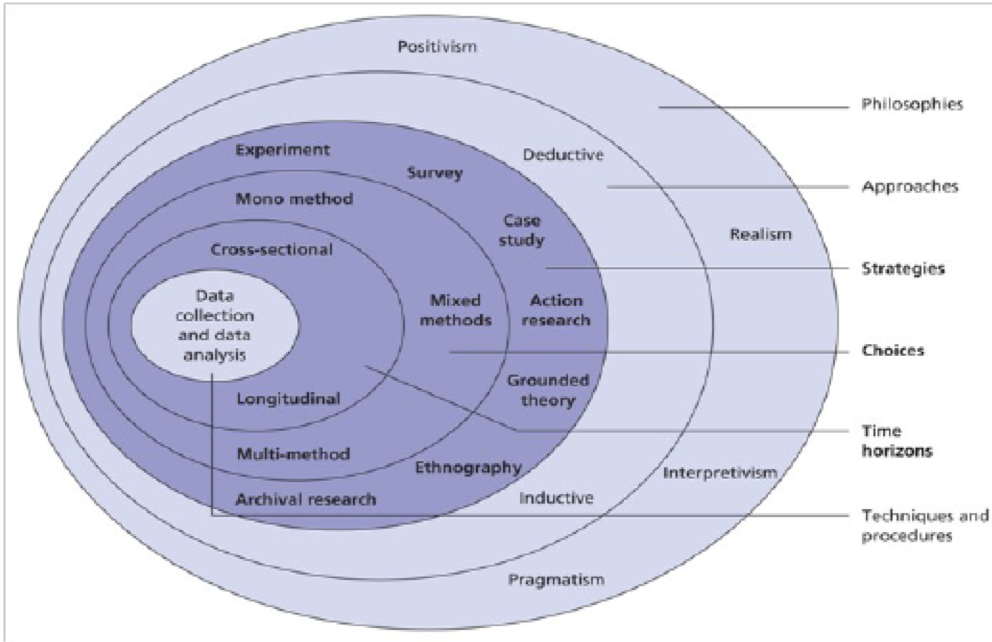
Based on the research questions in Chapter 3, Chapter 4 presents the research design regarding the research paradigm, epistemology, approaches, strategies, sample, data collection, and analysis techniques. To ensure the reliability, generalizability, and validity of the research results, challenges related to these criteria are also discussed. The chapter also justifies the attempts to improve the research quality with respect to the reliability, generalizability, and validity of the findings.

4.1 PROPOSED RESEARCH DESIGN

With an aim to investigate the research questions in Chapter 3, this section is devoted to the research design. Based on the research onion by Thornhill et al. (2009), the section proposes the research design of the thesis with relevance to the research paradigm, epistemology, approaches, strategies, sample, data collection, and analysis techniques. The summary of the proposed research design is presented as follows.

In the previous chapter, the proposed research questions are classified as exploratory questions. Exploratory research aims at investigating the nature of the problem to be solved (Onwuegbuzie & Leech, 2007; Patton, 1990). This document relies on the research onion (Thornhill et al., 2009) to set the foundation for the research design. Accordingly, each layer of the research onion including philosophies, approaches, strategies, data collection, and analysis is identified (Figure 4.1).

Figure 4.1
Research onion



Source: Thornhill et al. (2009)

Research partnerships are also established to facilitate the research design of the thesis. Accordingly, two organizations in the cultural sector in the region of Quebec, Canada are selected as the studied cases. Table 4.1 summarizes the proposed research design. Detailed explanations are presented in the following sections.

Table 4.1
Proposed Research Design

Research Design	**Descriptions**
Research type	Exploratory research
Paradigm and Philosophy	Qualitative / Social constructionism
Epistemology	Subjectivism
Approaches	Induction
Strategies	Case study
Sample	Alpha Organization and Beta Organization
Data collection	Documentary analysis, Observations, Semi-structured interviews
Data analysis	Intra-case analysis, Inter-case analysis, and Thematic analysis

Source: Dam (2021)

4.2 METHODOLOGICAL POSITION AND APPROACH

This section focuses on the methodological position and approach of the thesis. In this regard, the research paradigm and philosophy are clarified to explain the belief system of researchers (Robson & McCartan, 2016). Subsequently, the section explains the research epistemology in understanding how researchers approach and justify knowledge. Finally, the research approach justifies the induction of the thesis.

4.2.1 Research paradigm and research philosophy

A research paradigm is defined as the fundamental belief system of researchers, which influences their assumptions and perceptions (Robson & McCartan, 2016). On the flip side, research philosophies are beliefs or views of how knowledge is gathered, analyzed, and used (Lincoln, 2001; Schwandt, 1994). Building from these reflections, the section presents the justification of the research paradigm and philosophy of the thesis.

As the thesis aims at applying customer intelligence for marketing benefits in the cultural sector, the author classifies his research paradigm as qualitative. Considering the formulation of the research questions, the *"how"* question is also a typical form of a question in qualitative research (McCaslin & Scott, 2003). Qualitative research, which is primarily exploratory research, is usually used to explore, describe and understand real-world problems (Palys & Atchison, 2012). Correspondingly, the two research questions of the thesis proposed in Chapter 3 are formulated as the "how" question. The first research question focuses on how to transform customer data into customer intelligence in the age of big data considering the context of SMEs/SMOs in the cultural sector. On the other hand, the second research question explores how to apply customer intelligence to achieve marketing benefits in the context of SMEs/SMOs in the cultural sector. With the purpose to learn about customer intelligence and its applications for marketing benefits, these research questions have identified the research paradigm of the thesis as qualitative (Robson & McCartan, 2016). Qualitative research provides insights into the problem and helps researchers understand the richness of the research phenomenon (Bryman, 2007). Consequently, the research purpose of the thesis is in line with the nature of qualitative research. Qualitative research would be appropriate to study and explore the applications of customer intelligence for marketing benefits in the cultural sector.

Under the philosophical underpinnings of qualitative research, this thesis is based on social constructionism, in which knowledge is constructed through interactions among people in a society (Robson & McCartan, 2016). Knowledge or "reality" is not a separate existence (Schwandt, 1994). It is constructed by people's interactions and involved in different interpretations. The tasks of researchers as constructivists are to understand and explain various meanings and knowledge that are socially constructed (Lincoln, 2001; Schwandt, 1994). Therefore, constructivists are sometimes referred to as interpretivists who are in charge of interpreting the "reality" (Robson & McCartan, 2016). The author sets the foundation of the research philosophy as social constructionism because customer intelligence is constructed through the interactions of customers and service providers via digital platforms. According to the constructionist approach, customer intelligence cannot exist on its own. Moreover, customer intelligence is socially constructed on social networks and websites (Iglesias et al., 2018; Lau et al., 2014).

4.2.2 Research epistemology

Epistemology explains the way that researchers assume, perceive, and justify knowledge (Robson & McCartan, 2016). This section presents different types of research epistemology to understand how researchers approach the nature of social science. Upon the different types of research epistemology, the section justifies the choice of the constructionist approach.

Intending to clarify researchers' assumptions about the nature of social science, Burrell and Morgan (1979) divided epistemology into four separate social-scientific paradigms, including functionalist, interpretive, radical humanist, and radical structuralist, based on the two dimensions of subjective-objective and radical change-regulation. These four paradigms demonstrate mutually exclusive views on the social world. The study of Burrell and Morgan (1979) indicates that the sociology of regulation focuses on the status quo and social order whereas the sociology of radical change refers to radical change, conflict, and domination. The objectivism dimension believes that social entities exist independently; on the contrary, the subjectivism dimension infers that the nature of the social world is formed by different perceptions and interactions of social actors. In terms of epistemology, the objectivist approach to social science is referred to as positivism whereas the subjectivist approach is labeled as anti-positivism, interpretivism, or constructionism (Burrell & Morgan, 1979; Robson & McCartan, 2016).

Based on the constructionist approach, this study emphasizes the significance of subjectivism as a reality that can be differently interpreted by constructionists' viewpoints (Gergen, 2009). As revealed from the literature review, the application of customer intelligence for marketing benefits also depends on different perspectives such as leadership, management, organizational culture, and structure (Davenport & Spanyi, 2019; Gibbert et al., 2002; Reijonen & Laukkanen, 2010). Therefore, the research focus on the applications of customer intelligence for marketing benefits would fit the subjective nature of constructivism.

4.2.3 Research approach

The research paradigm and epistemology have set the foundation for the research approach of induction. Consequently, the section aims at presenting the justification of the inductive approach of the thesis.

As the research paradigm of the thesis is qualitative, an inductive approach is relevant for data collection as it is the typical feature of qualitative social research (Robson & McCartan, 2016). The inductive approach is described as a method to collect data and develop them into a theory (Lincoln, 2001; Palys & Atchison, 2012). In other words, the inductive approach goes from the specific to the general. The nature of studying from the specific to the general of the inductive approach is pertinent to the thesis since there are many factors under the three dimensions of management, science, and engineering that can influence the applications of customer intelligence for marketing benefits. The study of different specific factors can be developed into different generalizations on customer intelligence in various settings. In addition, the focus of the thesis on the cultural sector is also relevant to the nature of the inductive approach as it can be considered as the specific case for the application of customer intelligence for marketing benefits. Other applications of customer intelligence in different sectors would enhance the generalizability of the proposed model of customer intelligence for marketing benefits in Chapter 3.

4.3 RESEARCH STRATEGY

Given the nature of qualitative research, the author proposes the strategies of the case study to correspond to the research questions. Reasonings for these research strategies are presented in the following subsection. In addition, this section also examines the research time horizon, the sampling technique, and the sample of the thesis.

4.3.1 Case study

To reinforce the selection of the case study strategy for the thesis, the section provides an overview of this strategy (Bassey, 1998; Yin, 2003). Subsequently, the section presents the justification of the case study strategy of the thesis. Considering the single and multiple case study strategy, the section further justifies the choice of the multiple case study strategy which is relevant for the research objectives and the nature of the cultural domain.

A case study uses multiple sources for data collection to empirically investigate a phenomenon in a real-life context (Baxter & Jack, 2008). In the case that researchers want to gain a rich understanding of the research context, a case study will be an ideal strategy (Flyvbjerg, 2006). A case study is considered an empirical investigation to explore research questions formulated with the *Why*, *What*, and *How* questions (Robson & McCartan, 2016). It is noted that collecting and triangulating different sources of data are important for the case study strategy (Tellis, 1997). In this strategy, triangulation refers to the application of different data techniques to gain a comprehensive understanding of the phenomenon (Yin, 2015). Triangulation increases the validity of case studies as it examines the convergence of data from various data sources (Robson & McCartan, 2016).

The case study strategy is useful for the pursuit of the purpose of this thesis as it is a valuable tool of qualitative research to bring better clarification of a complex issue or a particular contemporary phenomenon (Thornhill et al., 2009). Considering the format of the research questions of this thesis, the case study strategy is optimal to respond to these questions as its objective of the case study is to gain insights into the complexity of the research phenomenon through multiple methods for collecting data (Baxter & Jack, 2008; Yin, 2003). With the support of various data sources including qualitative and quantitative data, researchers are likely to achieve the richest understanding of the research phenomenon (Scholz & Tietje, 2002; Tellis, 1997). Traditionally, the case study strategy implicates qualitative methods to gain rich information on a phenomenon (Scholz & Tietje, 2002). Therefore, this thesis adopts the case study strategy from the qualitative perspective to understand the complexity of the cultural sector in a comprehensive way.

The case study strategy can be either single or multiple (Yin, 2003). A single case study is often chosen to present a unique or extreme phenomenon (Robson & McCartan, 2016). For example, the domain of performing arts of the cultural sector can be studied as a single case study as this domain has caught more attention during the COVID-19 pandemic due to the nature of direct contact with customers. From this perspective, each cultural organization or cultural domain can serve as a specific case. On the other hand, the strategy for multiple case studies might be appropriate to study different cultural domains or organizations. The multiple case studies strategy will allow researchers to look at SMEs/SMOs in the cultural sector from different angles. Bearing in mind the various domains in the cultural sector, this thesis adopts the multiple case studies strategy. This strategy allows researchers to evaluate several cases to analyze within each setting and across settings (Thornhill et al., 2009).

4.3.2 Research time horizons

Once the research strategy is identified, it is necessary to determine the research time horizon (Baxter & Jack, 2008; Yin, 2015). Therefore, an overview of research time horizons is presented to highlight the difference between cross-sectional and longitudinal studies. Afterward, the section justifies the choice of the cross-sectional time horizon considering the research objectives.

The research time horizons can be either cross-sectional or longitudinal (Robson & McCartan, 2016). Cross-sectional studies examine a particular phenomenon at a snapshot time, whereas longitudinal studies continue over a given period (Flyvbjerg, 2006; Tellis, 1997). The purpose of cross-sectional studies is to compare different variables at the same time (Bassey, 1998; Yin, 2003). However, cross-sectional studies fail to view the change of variables before or after the snapshot is taken. Unlike cross-sectional studies, longitudinal studies focus on the same cases at two or more different time intervals to detect developments or changes (Thornhill et al., 2009). Therefore, longitudinal studies can establish a sequence of events. Both cross-sectional and longitudinal studies are observational (Baxter & Jack, 2008; Yin, 2003). This infers that researchers are not allowed to interfere with their research subjects or study environment (Flyvbjerg, 2006; Thornhill et al., 2009).

The thesis adopts the cross-sectional time horizon as the research objectives which aim at examining the application of customer intelligence for marketing benefits in the context of SMEs/SMOs in the cultural sector. In this light, the cross-sectional time horizon enables the author to compare different variables, including customer data, customer analytics, customer intelligence, and marketing benefits at the time of adopting customer intelligence. The next section will further explore potential data collection techniques that the thesis may apply.

4.3.3 Sampling techniques

This section aims at clarifying different types of non-probability sampling techniques in qualitative research. On this subject, the four types of sampling techniques including quota, purposive, volunteer, and haphazard sampling are clarified. The section ends with the justification of the purposive sampling technique for the thesis.

Qualitative research complied with non-probability sampling, including quota, purposive, volunteer, and haphazard sampling. Firstly, *quota sampling* sets a quota for the population based on the relevance and availability of data (Thornhill et al., 2009). Structure interviews often apply the quota sampling technique to choose a sample in an entirely non-random way. The advantage of quota sampling is cost-effective and time-saving (Sharma, 2017). Data can be collected quickly. Quota sampling is suitable for a large population as it stratifies the population into specific groups (Robson & McCartan, 2016). Then researchers apply certain criteria to calculate a quota for each group. Secondly, *purposive sampling* is also known as judgemental sampling as it relies on judgment to select cases that respond to the research questions and objectives (Baxter & Jack, 2008; Palys & Atchison, 2012). Accordingly, the selected cases are particularly informative. Purposive sampling techniques group these informative cases into different types, including extreme, heterogeneous, homogeneous, critical, typical, and theoretical cases (Patton, 1990). Literature acknowledges a significant amount of the grounded theory adopts the purposive sampling. Thirdly, *volunteer sampling* consists of snowball and self-selection sampling. Snowball sampling puts trust in the members of the desired population to recommend other potential members (Palys & Atchison, 2012; Patton, 1990). This sampling technique is often used in a case when it is difficult to find relevant cases. On the other hand, volunteer sampling happens when individuals express their willingness to participate in the research (Robson & McCartan, 2016). Participants' volunteer arises from their interests in the research topic. Lastly, *haphazard sampling* is also known as convenience sampling. Cases are selected because they are available (Robson & McCartan, 2016). Participants who are randomly interviewed at a shopping center or a public place would be a great example of haphazard sampling (Palys & Atchison, 2012; Patton, 1990). The advantage of this sampling technique is easy, fast, and cost-effective. On the flip side, haphazard sampling is criticized for low credibility (Thornhill et al., 2009). The results from haphazard sampling cannot represent the target population.

In this thesis, the sampling technique for interviews is purposive as the author relies on judgment to respond to research questions and objectives. Specifically, the purposive sampling technique is heterogenous, which focuses on subgroups of the target population (Robson & McCartan, 2016). The heterogenous sampling chooses participants with different characteristics to gain insights into subgroups (Baxter & Jack, 2008; Palys & Atchison, 2012). This thesis examines the cases of the domain of performing arts, and museums subgroups of the cultural sector due to their contrast in nature. The nature of the performing-arts domain is the direct consumption of live performances whereas the museum sector focuses on exhibitions. The selected organizations represent the typical and distinguished adoption of customer intelligence for marketing benefits. The next part of the thesis describes the selected cases as the sample of the thesis. The reasoning for each case is also discussed to strengthen the validity of the thesis.

4.3.4 Sample

Based on the purposive sampling technique, this section continues with the selected sample of the thesis. The sample is described in detail with the selection criteria. Based on these criteria, organizations Alpha and Beta are selected. Justifications for selecting Alpha and Beta are also presented in this section.

A sample is defined as a set of individuals, organizations, or objects that are selected from the target population (Heaton, 1998; Patton, 1990). With the focus on the cultural sector as the target population, the thesis relies on the purposive sampling technique to identify cultural organizations including organizations Alpha and Beta that are located in the region of Québec, Canada. The first selection criterion is that sample units belong to the cultural sector. According to the classification of UNESCO[5], Alpha represents

[5] https://en.unesco.org/creativity/files/cultural-economy-unescos-framework-cultural-statistics

the Performances and Celebration domain whereas Beta exemplifies the Cultural and Natural Heritage. The second criterion is that sample units are small and medium-sized enterprises or organizations. In terms of business size, the number of employees that SMEs/SMOs can employ must be less than 250 (OECD, 2020). Accordingly, SMEs/SMOs are divided into 3 categories: micro enterprises (fewer than 10 employees), small enterprises (10 - 49 employees), and medium enterprises (50 - 249 employees). Based on these categories, Alpha and Beta are small organizations. Combining the two sample criteria, organizations Alpha and Beta are selected as they are small organizations in the cultural sector. Table 4.2 provides a detailed description of Alpha and Beta.

Table 4.2
Description of the studied cases

	Alpha	**Beta**
Domain	Performing Arts (Performance and Celebration	Museums (Cultural and Natural Heritage)
Products / Services	Theatre Shows	Exhibitions
Number of employees	11-50 employees	11-50 employees
Year of foundation	1973	2001
Type	Non-profit	Non-profit

Source: Adapted from the sites of Alpha and Beta

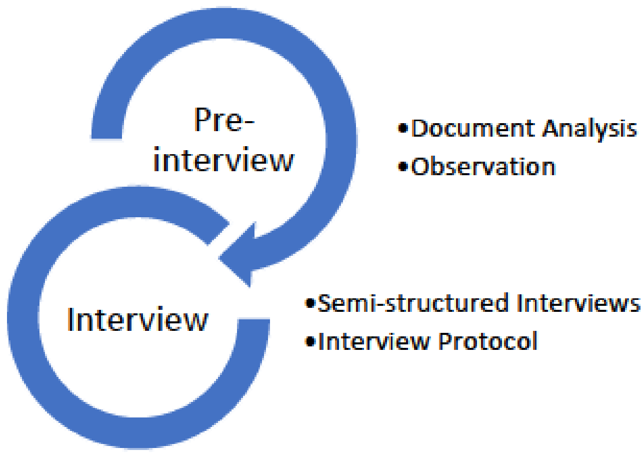
Alpha is a theatre in Montréal, Canada that offers five shows each season at Place des Arts. As a tourist attraction in Montreal, Alpha has innovated and made it accessible to live art performances. The majority of performances deal with essential themes of life, cultural, and social concerns. Alpha is chosen to participate in the interview as it belongs to the domain of performing arts in a populated urban agglomeration in North America, one of the significant domains of the cultural sector. The performing arts domain is also one of the most vulnerable domains in the cultural sector (UNESCO, 2020). Therefore, research on the case of Alpha would be a critical case for other cultural organizations in the regions. Despite being a non-profit organization, the theatre is also under financial pressure. Moreover, Alpha always strives for the financing of research and creative laboratories to promote innovation. Compared to other cultural organizations in the local region, Alpha is considered a digital pioneer as the theatre has recognized the importance of digitalization and has promoted the webcasting project as a part of its business strategy. This motivates the selection of Alpha as a case study due to their willingness and desire to take advantage of customer intelligence to improve financial performance and support product/service innovation.

Beta, which is a museum dedicated to Québécois culture, is located in downtown the Trois-Rivières city, Québec. Organization Beta bears witness to Québec society and studies its evolution. The objective of this organization is to develop, promote and make accessible to exhibitions in the domain of museums. In addition to exhibitions, Beta also offers room rentals for conferences, training, cocktails, etc. to diversify incomes. Consequently, the case of Beta would reveal interesting facts due to the different characteristics of the museum domain compared to the arts performing domain. In addition, the Covid-19 pandemic has brought challenges to the presentation of exhibitions. Beta is under pressure for transferring some of its activities to digital platforms without compromising the experience of visitors. This stimulates the need for customer intelligence to support Beta in the process of digitalization.

4.4 DATA COLLECTION FOR THE CASE STUDY STRATEGY

As depicted in Figure 4.2, data collection for the case strategy consists of two phases: pre-interview and interview (Robson & McCartan, 2016; Tellis, 1997). The pre-interview phase conducted document analysis and observation to better understand the studied phenomenon. The interview phase focuses on developing the interview protocol and conducting semi-structured interviews. The following part clarifies these two phases of the data collection process.

Figure 4.2
Phases of data collection



Source: Dam (2021)

4.4.1 Pre-interview phase

In terms of data collection techniques for the case study strategy, qualitative applies document analysis and observation before interviews (Robson & McCartan, 2016; Tellis, 1997). This section the process of document analysis and observation to prepare for the interview phase.

Before interviews, documentary analysis happens to understand participants and add richness to interpret collected data from interviews (Thornhill et al., 2009). Documentary analysis involves the analysis of internal and external documents such as archival records, reports, and newsletters (Yin, 2003). Documentary analysis can be considered an unobtrusive or non-reactive measure when documents are not directly generated for research purposes (Robson & McCartan, 2016). The most common technique in documentary analysis is the content analysis which is defined as "the systematic, objective, quantitative analysis of message characteristics" (Neuendorf & Kumar, 2015). The content analysis focuses on the analysis of texts, images, maps, symbols, sounds, and numerical records then groups and codes similar contents as a separate category (Neuendorf & Kumar, 2015; Robson & McCartan, 2016). During the residence in enterprises and meetings with the cultural organizations that are selected as studied cases, the author acquired various reports along with various data from sales, Google Analytics, Facebook, and other internal sources. These reports and data better understand the current situation of these organizations as well as their needs and capabilities for adopting customer intelligence for marketing benefits.

The observation technique involves watching, describing, analyzing, and interpreting what is observed (Robson & McCartan, 2016). There are two types of observations: participant observation and structure observation (Robson & McCartan, 2016). While participant observation focuses on interpreting the meaning of observed actions, structure observation emphasizes the frequencies of actions (Aktinson & Hammersley, 1998). In light of the research purpose of this study, the author conducted participant observation through his residence in enterprises and meetings with the studied cultural organizations. Conducting a participant observation allows researchers to actively participate in the activities of research subjects (Robson & McCartan, 2016). Researchers can become a member of the organization or the experimental situation; they have a chance to learn the social and 'symbolic' world of the observed group (Aktinson & Hammersley, 1998; Thornhill et al., 2009). Therefore, they are likely to interpret actions and gain valuable insights. In fact, the author has a chance to participate in many meetings with cultural organizations. During these meetings, the author has observed significant information to understand relevant perspectives of cultural organizations related to the research topic.

4.4.2 Interview phase

For the interview phase, semi-structured interviews are conducted to collect data. This section justifies the motivations for interviews and then provides a description related to the form, duration, and place of interviews. The number of interviews is also examined to ensure the validity and reliability of the research results. Afterward, the interview protocol is presented with relevant themes. The section ends with a grid of interview questions, research objectives, and research constructs.

Normally, semi-structured and unstructured interviews are applied in qualitative research to gain in-depth responses (Blee & Taylor, 2002; Palys & Atchison, 2012). Semi-structured interviews have a list of open-ended questions or themes to stimulate responses from participants (Blee & Taylor, 2002). On the other hand, unstructured interviews, which are also referred to as in-depth interviews, have no predetermined list of questions (Thornhill et al., 2009). As the literature review has disclosed relevant themes on customer intelligence for value creation in marketing, semi-structured interviews show great potential as a data collection technique. Conducting the interviews based on a formalized list of open-ended questions instead of structured and closed-ended questions allows new ideas to be brought up while not losing track of the interviews (Robson & McCartan, 2016). Semi-structured interviews encourage two-way communication while providing an opportunity for opening up sensitive issues and gaining more in-depth information (Aktinson & Hammersley, 1998; Thornhill et al., 2009).

Interviews can happen one-to-one or in a group setting as focus groups (Blee & Taylor, 2002; Qu & Dumay, 2011). One-to-one interviews can be conducted face-by-face, by telephone, or on the Internet (e.g.: in virtual meetings) (Qu & Dumay, 2011). On the flip side, a focus group can have between 2 to 12 participants depending on the complexity of the research topic, the skills of the interviewers, and the nature of the interviewees (Qu & Dumay, 2011; Thornhill et al., 2009). Similar to one-to-one interviews, focus groups can be conducted face-to-face or via the Internet. In this study, semi-structured interviews are conducted via Zoom at the convenience of managers and directors of organizations Alpha and Beta with the duration of approximately 90 minutes. Regarding research ethics, the ethics certificate is also acquired from UQTR to comply with ethical standards and requirements. The proof of the ethics certificate can be found in Appendix B of the thesis. An agreement of data non-disclosure is also attached in Appendix C. Table 4.3 describes interviewees of the organizations Alpha and Beta along with the interview duration.

Table 4.3
Description of interviews

<table>
<tr><th>Organizations</th><th>Interviewees</th><th>Interview Duration</th></tr>
<tr><td rowspan="4">Alpha</td><td>Director of Communications and Marketing</td><td rowspan="4">1 hr and 30 minutes</td></tr>
<tr><td>Sales and Customer Service Manager</td></tr>
<tr><td>Digital Project Manager</td></tr>
<tr><td>Research Analyst</td></tr>
<tr><td rowspan="2">Beta</td><td>Communications and Marketing Manager</td><td rowspan="2">1 hr and 50 minutes</td></tr>
<tr><td>General Director</td></tr>
</table>

Source: Dam (2021)

Concerning a suitable sample size, there are no rules to decide the exact number of sample sizes for non-probability sampling techniques (Baxter & Jack, 2008; Qu & Dumay, 2011). In qualitative research, the sample size is subject to research questions and objectives. To put it in another way, the sample size depends on what researchers need to figure out, the extent of credibility, and the availability of resources (Palys & Atchison, 2012; Qu & Dumay, 2011). Furthermore, gaining insights from collected data is more important than the sample size (Patton, 1990). Concerning this research, the author continues to conduct additional interviews until data is saturated to ensure the validity of research results (Baxter & Jack, 2008; McCaslin & Scott, 2003). Data saturation is the stage where no new or little information is revealed from additional interviews (Thornhill et al., 2009).

The interview protocol plays an important role in guiding the process of information collected during interviews (Baxter & Jack, 2008; McCaslin & Scott, 2003). To develop a protocol for interviews, the author prepares an interview guide on customer intelligence for marketing benefits with various themes associated with interview questions and probes. Probes are hints for interviewees to explain or build on their responses (Thornhill et al., 2009). Probes help interviewers add significance and depth to the collected data. The order of interview questions can be varied based on the flow of discussions and the logic of questioning. The interviewer aims at generating a friendly environment to stimulate the natural flow of ideas and opinions. Important points when conducting an interview are also summarized as followed (Robson & McCartan, 2016):

- Explaining the purpose of an interview.
- Asking permission for recording the obtained data.
- Ensuring the privacy and anonymity of the interview
- Starting with a relevant theme.
- Using probing questions to clarify points and support more explanation.
- Listening actively with appropriate nonverbal language.
- Facilitating the flow of discussion and ensuring that all relevant themes are covered.

Table 4.4
Interview guide

Themes	Interview Questions and Probes
Introduction	• Greetings • Thank you for your participation • Confirming the anonymity and privacy • Explaining the meaning of customer intelligence developed from the thesis Question: Would you please tell me about your organization, sector, and competitors.
Theme 1: Needs for customer intelligence	**1.1 What are the marketing challenges that your enterprise/organization is facing?** **Probe:** Do you have any difficulty with the decision-making process? **Probe:** Do you have any difficulty in satisfying customers? **1.2 How would your enterprise/organization adapt to challenges due to the age of big data?** **Probe:** Has your enterprise/organization adapted the business model? **Probe:** How do you take advantage of customer data to support the decision-making process?
Theme 2: Sources and types of customer intelligence	**2.1 What types of customer intelligence does your enterprise/organization rely on for the decision-making process?** **Probe:** Do you collect customer intelligence on demography, behaviors, psychology, or values of customers **2.2 Considering the importance of customer data in the era of big data, what types of customer data does your enterprise/organization need for the decision-making process?** **Probe:** Do you need customer data related to their demography, behaviors, interactions, satisfaction, or transactions? **Probe:** Are there any other types of customer data that you collect? **2.3 What sources of customer data does your enterprise/organization collect? E.g.: from internal/external sources, the website of the company, or social media?**

Themes	Interview Questions and Probes
	Probe: Do you collect clickstream data on the website of the company or Google Analytics? **Probe:** Do you pay attention to customer behaviors through likes, shares, number of follows, or hashtags on social media?
Theme 3: Applications of customer intelligence for marketing benefits	**3.1 What is the application of customer intelligence related to customers?** **Probe:** How about customer satisfaction, segmentation, profiling, attendance? **3.2 What is the application of customer intelligence related to products/services?** **Probe:** How about product/service development and innovation, sales, cross-selling? **3.3 What is the application of customer intelligence related to experience on the web and social media?** **Probe:** How about customer awareness, customer engagement, customer conversion, and customer loyalty? **3.4 What is the application of customer intelligence related to value creation?** **Probe:** How about customer lifetime value, customer value, customer co-creation? **3.5 Is there any application from customer intelligence that you would like to mention?**
Conclusion	**Do you have any other points to add that we have not touched on?** ➔ **Let the respondent speak on one or more subjects he/she cares about.**

Source: Dam (2021)

Table 4.4 presents the three themes that are identified from the literature review in Chapter 2. The first theme of the interview will focus on the need for customer intelligence. This part of the interview verifies challenges faced by enterprises/organizations, which stimulate the need for customer intelligence. The first question examines if cultural organizations are aware of their current challenges in marketing. The second question explores how they adapt to changes in the age of big data, specifically in taking advantage of customer data to support marketing decisions.

The second theme of the interview will clarify types of customer intelligence along with data sources. The interview questions aim at understanding what specific types of customer intelligence are applied to cultural SMEs/SMOs. This theme also elucidates the external and internal sources that cultural SMEs/SMOs rely on to acquire customer intelligence. The third theme aims at the application of customer intelligence for value creation in marketing. Several questions are posed to clarify the support of customer intelligence related to products, customers, experience on the web and social media, and value creation. Other potential applications of intelligence are also explored.

To ensure integration with the research objectives, all the interview questions are aligned with the research objectives along with research constructs. These research constructs are developed from the literature in Chapter 2. Table 4.5 provides the grids of research objectives, interview questions, and research constructs.

Table 4.5
A grid of research objectives and interview questions

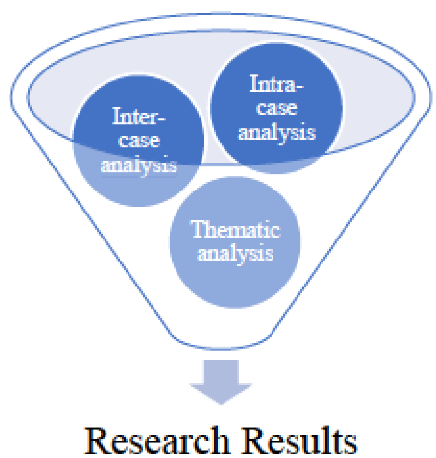
Interview Questions	1.1	1.2	2.1	2.2	2.3	3.1	3.2	3.3	3.4	3.5
Research objective 1 – Customer intelligence (CI)										
1.1 Types of customer intelligence			X							
1.2 Types of customer data				X						
1.3 CI from digital platforms					X					
Research objective 2 – Applications of customer intelligence										
2.1 Marketing benefits						X	X	X	X	X
2.2 Need for CI	X	X								
Research constructs										
Customer intelligence	X		X	X	X					
Customer data				X	X					
Customer analytics				X	X			X		
Marketing benefits						X	X	X	X	X

Source: Dam (2021)

4.5 DATA ANALYSIS

Once data are collected from interviews, they are thenceforth analyzed to reveal findings on the studied cases. To analyze data, this section presents the data analysis approach and technique (Figure 4.3). The data analysis approach will discuss two levels of analysis, including intra-case analysis and inter-case analysis (Della Porta, 2008; Ragin, 2004). Then the section continues with the thematic analysis to analyze the content of themes and interrelationships among themes based on interview data (Braun & Clarke, 2006; Maguire & Delahunt, 2017).

Figure 4.3
Data analysis



Source: Adapted from Della Porta (2008) and Ragin (2004)

4.5.1 Data analysis approach

The section discusses two levels of data analysis: intra-case analysis and inter-case analysis. The intra-case analysis aims at exploring findings within a case whereas the inter-case analysis compares the difference and similarities among cases (Della Porta, 2008; Ragin, 2004). Justifications of the intra-case analysis and inter-case are also presented as follows.

The intra-case analysis relies on pattern matching as a common strategy to compare the interview data of the case with the conceptual model (Tellis, 1997; Yin, 1981). This comparison reveals if the empirical data cover all constructs developed in the conceptual model. The intra-case analysis serves as an abductive approach to enrich the conceptual model regarding the empirical reality (Baxter & Jack, 2008; Qu & Dumay, 2011). Based on the analysis of empirical data, researchers can better understand each construct in the conceptual model (Heaton, 1998; Scholz & Tietje, 2002). Furthermore, intra-case analysis can reveal relevant constructs that can influence the research results. To make sense of constructs in the conceptual model, the intra-case analysis gives prominence to the narrative strategy to communicate the richness of the studied case in an organized and chronological order (Baxter & Jack, 2008; Patton, 1990). Different types of tables and graphs are often used to provide descriptive statistics to facilitate the understanding of conceptual models. Finally, each construct of the conceptual model is analyzed to gain an in-depth understanding of the studied case (Patton, 1990; Thornhill et al., 2009).

Considering the CIMB model in Chapter 3, the intra-case analysis would be an optimal choice as it aims at verifying the model to understand the applications of customer intelligence for marketing benefits. Subsequently, the constructs of the CIMB model, including customer data, customer analytics, customer intelligence, and marketing benefits will be examined in detail. Each case would reveal interesting findings regarding the applications of customer intelligence for marketing benefits in their cultural domains. The similarity and difference in each cultural domain would prompt the motivation for the inter-case analysis which is also the next step of the analysis process.

Inter-case analysis which is also known as cross-case or cross-sectional analysis to gain a profound understanding of studied cases (Patton, 1990; Thornhill et al., 2009). Another advantage of the inter-case analysis is to improve the generalizability of research results (Tellis, 1997; Yin, 1981). The inter-case analysis takes into consideration the similarity and differences in interpreting each construct of the conceptual model among cases (Baxter & Jack, 2008; Scholz & Tietje, 2002). Researchers can also take a closer examination between pairs of cases to enrich understandings and have more powerful explanations (Baxter & Jack, 2008; Yin, 2003). Concerning strategies for inter-case analysis, the case-oriented strategy focuses on the cases to gain a thick description of a small number of cases (Della Porta, 2008). On the flip side, the variable-oriented strategy aims at examining statistical rules of constructs or variables of cases (Ragin, 2004). This thesis adopts the mixed strategy, which combines the case-oriented and variable-oriented strategy to provide a multi-facet investigation of the CIMB model.

The inter-case analysis would leverage the validity and reliability of the research results considering the nature of the cultural sector. The thesis attempts to investigate the cases in the domains of museums and performing arts. By adopting the mixed strategy, the thesis not only examines the similarity and difference among the cases but also investigates the variation among constructs of each case. Therefore, the findings from the studied cases are likely to generalize the nature of customer intelligence adoption for marketing benefits in the cultural sector. In other words, the inter-case analysis would add value to the research results and deal with the generalizability of the case study strategy.

4.5.2 Data analysis technique

To gain deep insight into the research topic, this section touches upon the overview of thematic analysis with the emphasis on the advantages as the justification for this technique. Subsequently, the six phases of thematic analysis are presented along with the demonstration of the coding process based on NVivo, a well-known qualitative data analysis software (Palys & Atchison, 2012; Zhang & Wildemuth, 2009).

The thematic analysis emphasizes the significance of themes and interrelationships among themes (Braun & Clarke, 2006; Maguire & Delahunt, 2017). In terms of data analysis, thematic analysis discovers concepts and relationships in data and organizes them in an explanatory theoretical scheme (Thornhill et al., 2009). Qualitative data, which are collected from interviews are analyzed through thematic analysis (Boyatzis, 1998). In qualitative research, thematic analysis is the most common method for identifying important patterns or themes (Maguire & Delahunt, 2017). It is also considered the foundational method for qualitative analysis. A common pitfall of thematic analysis is just summarizing and organizing data (Braun & Clarke, 2006). In fact, a good thematic analysis can interpret and make sense of different responses of interviewees (Palys & Atchison, 2012; Qu & Dumay, 2011).

Qualitative research has witnessed several studies that apply thematic analysis to intensively understand a research phenomenon in a given situation (Palys & Atchison, 2012; Patton, 1990; Zhang & Wildemuth, 2009). One of the advantages of thematic analysis is its flexibility (Maguire & Delahunt, 2017). Unlike other qualitative analysis techniques (for example, conversation analysis, and interpretative phenomenological analysis), thematic analysis is not tied to a particular theoretical or epistemological position (Thornhill et al., 2009). It is a flexible technique that can provide a rich, detailed explanation of data. In interpreting data, thematic analysis clarifies two levels of themes: semantic and latent (Braun & Clarke, 2006). The semantic level focuses on the explicit or surface meanings of the data, whereas the latent level gives prominence to the interpretation and explanation of what a participant said or what was written (Boyatzis, 1998). Ideally, the thematic analysis starts with the semantic level to summarize and organize patterns. Afterward, it should end with the latent level by theorizing the meanings, significance, and implications of the patterns (Patton, 1990).

There are six typical phases in thematic analysis (Boyatzis, 1998; Braun & Clarke, 2006; Maguire & Delahunt, 2017). Each phase is not necessarily in chronological order. Researchers should move back and forth among these phases when dealing with complex data. The detail of these phases is presented as follows.

- *Phase 1 – Familiarizing with Data.* The first phase of thematic analysis highlights the importance of familiarizing with the depth and breadth of the data set. It is recommended that researchers should read data many times before coding (Maguire & Delahunt, 2017). Particularly, researchers should read data in an active way by identifying the meanings of potential patterns (Braun & Clarke, 2006). It is also a good idea to take note of remarkable ideas to prepare for the coding process (Thornhill et al., 2009). In this step, it is important to transcribe verbal data (Bazeley & Jackson, 2013). Interviews need to be converted to verbatim to conduct a thematic analysis (Braun & Clarke, 2006; Maguire & Delahunt, 2017). A verbatim should consist of both verbal and non-verbal utterances which are true to the original nature of responses from interviewees (Boyatzis, 1998). Even though this step is time-consuming and frustrating, it is considered an important phase of thematic analysis in helping researchers develop a far more thorough understanding of data (Patton, 1990). In this study, the interviews are in French; therefore, the author translates the verbatims into English to suit the language of the thesis. Furthermore, the author has a French native speaker verify and improve the quality of translation.

- *Phase 2 – Generating Initial Codes.* Phase 2 commences with creating a list of interesting ideas that are found from data (Braun & Clarke, 2006; Patton, 1990). Based on the list, initial codes are produced. Codes are defined as basic segments of data that can reveal meaningful interpretations of the studied phenomenon. In the other words, coding is to categorize data into meaningful groups (Boyatzis, 1998; Maguire & Delahunt, 2017). Therefore, a code should be clear and concise with a well-defined scope (Patton, 1990). Researchers can code data based on either the entire content of the data set or research questions (Bazeley & Jackson, 2013; Boyatzis, 1998). In most cases, the coding process relies on the research questions to identify particular features of the data set. This process can be conducted either manually or by a software program such as Nvivo (Bazeley & Jackson, 2013). Table 4.6 presents the codes and their description which are extracted by Nvivo. Accordingly, each code corresponds with the number of coded files and references that mention it. Files are documents that are transcribed from the interviews whereas references are the coded content from interviews. Separate codes for each studied case can be found in the Appendix D and E of the thesis.

Table 4.6
Code description

Codes	Description	Files	References
Descriptive analytics	Methods calculate, describe, and summarize historical data	3	10
Experts	The use of experts to analyze data	1	3
Predictive analytics	Methods forecast future outcomes based on historical data	1	1
Support services or tools	The use of services and tools to support data analytics	2	8
Visualization	The graphic representation of data	1	2
Customer context	Context data related to location, timing, weather, and so on	2	4
Data characteristics	Traits related to volume, value, variety, velocity, and veracity	2	2
Data integration	Combining data from various sources	3	8
Data sources	Locations where data can be acquired	3	25
Data types	Demographic, behavioral, psychographic, and transactional data	3	12
Data updates	The modification of the existing data	1	1
Customer conversion	Potential customers take a specific desired action	1	11
Customer demography	Intelligence related to age, income, gender, profession, and so on	3	7
Customer engagement	Customer interactions on websites or social media	2	8
Customer experience	Customer behaviors through their journey on websites and social media	1	3
Customer satisfaction	The extent customers are happy with products or services	2	4
Product and service development	The process of creating new products/services	2	4

Codes	Description	Files	References
Product and service innovation	The process of innovating products/services	1	2
Customer journey	Different stages related to pre-purchases, purchases, and post-purchases	2	2
Customer preferences	Behaviors and purchase motivations of customers	2	4
Customer value	The economic, social, and cognitive value of customers.	1	3
Interactive dashboards	A data visualization tool that allows managers to interact with data	2	3
Segmentation	Dividing a business market into homogenous groups	3	11
Business goals	The target or business objectives that cultural organizations aim at reaching	2	11
Covid-19 challenges	Difficulties and pressure due to the Covid-19 pandemics	3	7
Customer needs	Motives that prompt customers to buy products/services or interact with enterprises	1	3
IT investment	Investment in information technology to adopt customer intelligence	2	4
Promotional strategy	Marketing plan to stimulate sales and other business objectives	3	6
Words of mouth	The passing of information among customers	1	2

Source: NVivo

- *Phase 3 – Searching for Themes.* Once the codes are identified in Phase 2, these codes are sorted to search for themes (Patton, 1990). A theme is defined as a pattern that is characterized by its significance in relation to the research questions or the data set (Baxter & Jack, 2008; Heaton, 1998). A theme is formed by analyzing and combining different codes (Qu & Dumay, 2011). At the end of phase 3, all codes are analyzed and organized to broader themes to respond to the research questions (Palys & Atchison, 2012). In general, a code fits into a particular theme. In some cases, a code can be associated with more than one theme (Patton, 1990). Furthermore, it is possible that some codes do not belong to any themes. In this case, researchers can put these codes in a miscellaneous theme (Thornhill et al., 2009). To facilitate the process of searching for themes, researchers can apply visualization techniques such as mind mapping, thematic maps, or tables to organize codes into theme piles

(Boyatzis, 1998). Figure 4.4 presents the coding scheme extracted by NVivo. Based on the interview guide, there are four key themes (corresponding to the key constructs), including customer data, customer analytics, customer intelligence, and marketing benefits. The fifth theme “other codes” covers different codes related to business goals, Covid-19 challenges, customer needs, IT investment, promotional strategy, and words of mouth that are identified from interviews.

Figure 4.4
Fitting themes for codes

Name	Files	References
Customer analytics	0	0
Descriptive analytics	3	10
Experts	1	3
Predictive analytics	1	1
Support services or to...	2	8
Visualization	1	2
Customer data	0	0
Customer context	2	4
Data characteristics	2	2
Data integration	3	8
Data sources	3	25
Data types	3	12
Data updates	1	1
Customer intelligence	0	0
Customer conversion	1	11
Customer demography	3	7
Customer engagement	2	8
Customer experience	1	3
Customer satisfaction	2	4
Product and service d...	2	4
Product and service in...	1	2
Marketing benefits	0	0
Customer journey	2	2
Customer preferences	2	4
Customer value	1	3
Interactive dashboards	2	3
Segmentation	3	11
Other codes	0	0
Business goals	2	11
Covid-19 challenges	3	7
Customer needs	1	3
IT investment	2	4
Promotional strategy	3	6
Words of mouth	1	2

Source: NVivo

- *Phase 4 – Reviewing Themes*. Phase 4 involves the refinement of preliminary themes in the previous phase (Thornhill et al., 2009). Accordingly, important criteria to define themes are internal homogeneity and external heterogeneity (Boyatzis, 1998; Heaton, 1998). Internal homogeneity ensures the coherence of data within a theme whereas external heterogeneity enables the distinction among themes (Boyatzis, 1998; Patton, 1990). To verify the internal homogeneity, it is important to read all the collated extracts for each predefined theme and make sure that these codes can fit into a coherent theme (Tellis, 1997). If not, researchers should rework preliminary themes by identifying their problems, redefining them into new themes, or discarding them (McCaslin & Scott, 2003; Patton, 1990). Once the internal homogeneity is ensured, researchers can move on with the external heterogeneity. The external heterogeneity confirms the validity of themes with the entire data set (Baxter & Jack, 2008; Yin, 2003). All the themes should be distinct while fitting together with respect to the entire data set. Lastly, this phase also ascertains any missing data to be coded to these themes (Patton, 1990).

- *Phase 5 – Defining Themes.* The purpose of phase 5 is to identify the significance of each theme and determine what aspects of the data set each theme represents (Boyatzis, 1998; Heaton, 1998). In this phase, the thematic map is usually applied to illustrate the relationships among themes. A defined theme should not be too complex or diverse (Patton, 1990). If this happens, it is necessary to go back to the previous phase to organize collated data extracts for each theme in a coherent manner (Boyatzis, 1998; Heaton, 1998). Following the view, a thematic map is created to portray the density of codes among themes. In this study, the thematic map is presented in the analysis section of Chapter 5 of the thesis. For each defined theme, a detailed analysis to describe the scope and content of each theme is also presented (McCaslin & Scott, 2003; Patton, 1990). Furthermore, each theme should tell a story about the entire story of the data set as well as the research questions (Thornhill et al., 2009).

- *Phase 6 – Writing Up.* Once all themes are well defined, phase 6 starts the task of writing up the thematic analysis as a part of a journal article or a dissertation (Tellis, 1997). The write-up aims to tell the story of the data set concerning the research questions (McCaslin & Scott, 2003; Patton, 1990). Accordingly, the write-up should be concise, coherent, and logical within and across themes (Boyatzis, 1998; Heaton, 1998). Researchers should prove the prevalence of each theme by providing sufficient evidence with data (Patton, 1990). The write-up should go beyond data description; instead, it should make an analysis or argument with relevance to the research questions (Boyatzis, 1998; Patton, 1990). Chapter 5 of the thesis presents the write-up of data description and analysis.

4.6 CRITERIA TO ASSESS RESEARCH QUALITY

To develop well-designed qualitative research, it is important to pay attention to data quality issues, including reliability, generalisability, and validity (Thornhill et al., 2009). This part of the thesis deals with data quality issues associated with the case study strategy in qualitative research.

4.6.1 Reliability

Reliability is defined as the standardization in qualitative research (Liu & Shi, 2015; Yin, 2003). Different biases from interviews that might influence the reliability of this strategy are discussed. The section also presents the attempt of the author in dealing with these biases.

Concerning the interview technique for data collection in the case study strategy, the variation in research results may arise due to issues of bias. There are three types of bias: interviewer bias, interviewee bias, and participation bias (Thornhill et al., 2009). Firstly, interviewer biases result from the verbal or non-verbal verbal languages of interviewers (Blee & Taylor, 2002; Qu & Dumay, 2011). For example, the tone of interviewers can influence the responses of interviewees. In many cases, interviewers may impose their beliefs through the way they ask questions (Baxter & Jack, 2008;

Yin, 2003). Similarly, they may interpret responses with personal bias. The second bias is interviewee or response bias (Robson & McCartan, 2016). This type of bias is caused by perceptions of interviewees about interviewers or interview topics. In the case of sensitive topics, interviewees may not feel comfortable with discussion (Baxter & Jack, 2008; Yin, 2003). Therefore, they tend not to reveal the full fact related to interview themes (Palys & Atchison, 2012; Patton, 1990). Finally, participation bias is caused by the nature of organizational participants (Thornhill et al., 2009). Particularly, the lengthy duration of interviews may cause bias in how interviewees respond to the interview questions (Baxter & Jack, 2008; Tellis, 1997). In some cases, interviewees can cause non-response bias by refusing to take part in the interview (Robson & McCartan, 2016).

To minimize biases from interviews, the methodological steps for collecting and analyzing data are prepared and proposed by the author as presented in the previous part of this chapter. Accordingly, an interview guide is developed to structure the interviews and ensure a consistent experience with all participants. The interview guide, which consists of standardized questions, also helps the interviewer avoid misleading information or losing track. Before interviews, the author conducts rehearsals and mock interviews to avoid any unnecessary biases. From the perspective of participants, they are well informed about the themes of the interviews so that they can feel comfortable answering all the questions.

4.6.2 Generalizability

This section continues with the challenge related to the generalizability in qualitative research. To deal with this challenge, the thesis conducts data triangulation and inter-case analysis to leverage the generalizability of the research results (Della Porta, 2008; Ragin, 2004).

Generalizability refers to the degree to which the research results can be applied to other settings or a broader group of people or situations (Thornhill et al., 2009). Therefore, generalizability is also called external validity (Robson & McCartan, 2016). A small sample in semi-structured interviews is often the main reason for generalizability (Blee & Taylor, 2002; Qu & Dumay, 2011). In general, the sample size in qualitative research is smaller than in quantitative research (Boyatzis, 1998; Heaton, 1998).

This thesis applies different strategies for data collection, including multiple case studies to recuperate the generalizability of the research results (Kozinets, 2002). Data are collected not only from interviews but also from document analysis and observations during the residence in enterprises. Therefore, data triangulation would deal with the generalizability in qualitative research (Robson & McCartan, 2016). Moreover, it is not necessarily true that the results of qualitative research are less likely to represent the population (Palys & Atchison, 2012; Qu & Dumay, 2011). The nature of qualitative research focuses on analyzing and interpreting insights of data (Baxter & Jack, 2008). Accordingly, the thesis adopts the intra-case analysis and inter-case analysis to add value to the generalizability of the research results (Della Porta, 2008; Ragin, 2004).

4.6.3 Validity

This section ends the chapter with a discussion on the challenge of validity as the accuracy of the research results (Liu & Shi, 2015; Yin, 2003). Different techniques to improve the validity are also implemented and presented in the following part.

Validity is the extent to which researchers gain access to the knowledge and experience of interviewees (Palys & Atchison, 2012; Patton, 1990). In other words, validity refers to the accuracy of the research results (Liu & Shi, 2015; Yin, 2003). To ensure validity, it is important to pay attention to the scope to clarify questions (Thornhill et al., 2009).

Another technique to better understand responses from interviewees is to use probes (Robson & McCartan, 2016). Finally, the case study strategy should rely on triangulation to improve the validity of the research. Triangulation is the application of different techniques or approaches by various researchers to gain a comprehensive understanding of the studied phenomenon (Baxter & Jack, 2008; Yin, 2015). The convergence of information in triangulation ensures the validity of research results (Palys & Atchison, 2012; Patton, 1990).

In an attempt to improve the validity of the research results, a grid of research objectives, interview questions, and research constructs was developed as illustrated in Table 20 to ensure the scope and alignment of interview questions. Besides, the probes for each interview question are proposed to deal with the challenge of validity. Finally, the thesis implements triangulation in data collection and analysis by acquiring different data sources and data analysis techniques to enhance the validity of the research results.

CHAPTER 5
RESEARCH RESULTS AND DISCUSSIONS

As a continuation of the proposed research design in Chapter 4, Chapter 5 presents the research results and discussions. The objective of this chapter is to analyze interview data in reflection to the CIMB model. Based on the analysis of the multiple case study, Chapter 5 discusses the current, emerging, and future practices of Alpha and Beta. The discussion section also verifies the applicability of the CIMB model in Chapter 3 by the demonstration of the interactive dashboards developed for Alpha and Beta. Chapter 5 ends with the recommendation on maturity levels of adopting customer intelligence based on the research results.

5.1 ANALYSIS OF THE MULTIPLE CASE STUDY

The multiple case study attempts to respond to verify and add value to the CIMB model that is proposed in Chapter 3. As presented in the proposed research design in Chapter 4, this section continues with the intra-case analysis of Alpha and Beta as the selected cases of the thesis. After the intra-case analysis, the inter-case analysis across the cases is implemented. In the intra-case and inter-case analysis, the thematic analysis technique is applied to gain in-depth insights into each construct of the CIMB model.

5.1.1 The intra-case analysis of Alpha

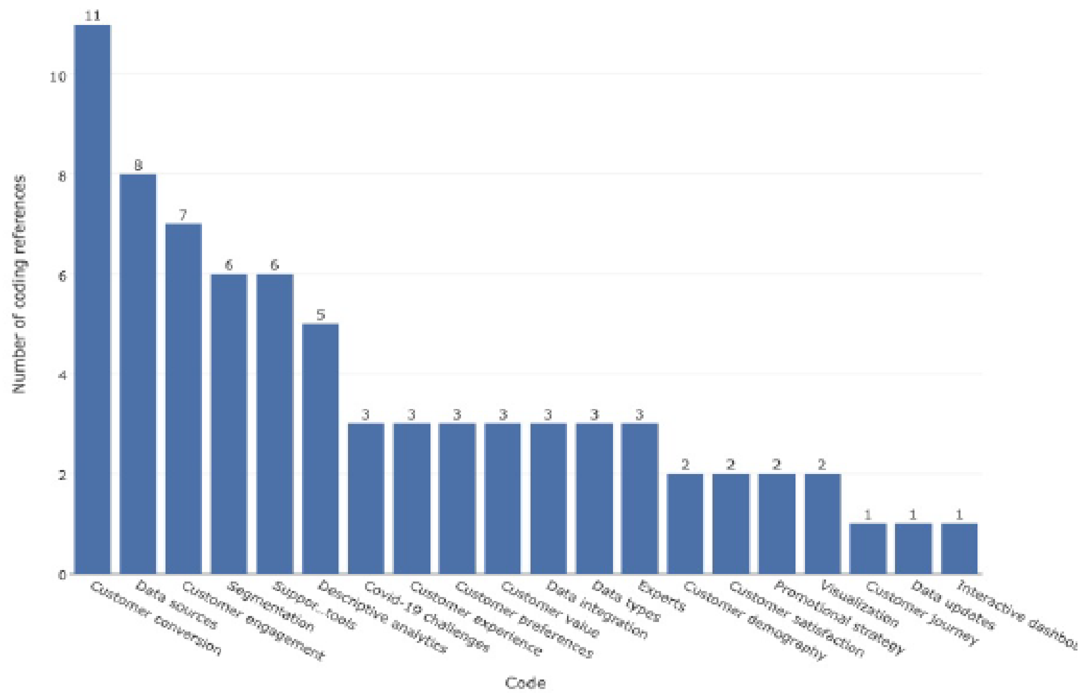
The section presents the case description and analysis of Alpha. The case description relies on the thematic analysis to present statistics relating to the codes, top coding references, and most frequent words based on the interview data. On the flip side, the case analysis aims at interpreting codes related to the constructs of the CIMB model.

5.1.1.1 Alpha case description

In this section, the thematic analysis is applied to define codes, top coding references, and most frequent words to provide a big picture of the case of Alpha.

The interview data collected from the case of Alpha produces 21 codes with 124 coding references or coded content. Figure 5.1 demonstrates the most frequent codes along with the number of coding references. The most significant proportions of coding references are related to "customer conversion", "data sources", "customer engagement", "segmentation", and "support services or tools". This indicates the attention of the managers and directors of Alpha with relevance to these codes. It seems that Alpha shows a great interest in adopting customer intelligence for marketing benefits concerning customer conversion and engagement. Furthermore, the code "data sources" with a high frequency of coding references gives a positive signal for acquiring data and turning them into customer intelligence. Detailed analysis of these codes concerning the constructs of the CIMB model is presented as follows.

Figure 5.1
Most frequent coding references of Alpha



Source: NVivo

Figure 5.2 demonstrates the top 100 words extracted from the interview data for the Alpha Case. The most frequent words are "data" (52 counts, or 0.93%) followed by "customer" (52 counts, or 0.93%), "information" (35 counts, or 0.63%), "business" (24 counts, or 0.43%), and "theatre shows" (23 counts, or 0.41%). This prompts the motivation of transforming customer data into information and applying it to business to improve customer satisfaction with theatre shows. Other interesting top words are "dashboard", "analytics", "decision", "cost", and "income" which indicate the interest of the managers and directors of Alpha. A list of top words with the number of counts and weighted percentage can be found in the Appendix F of this document.

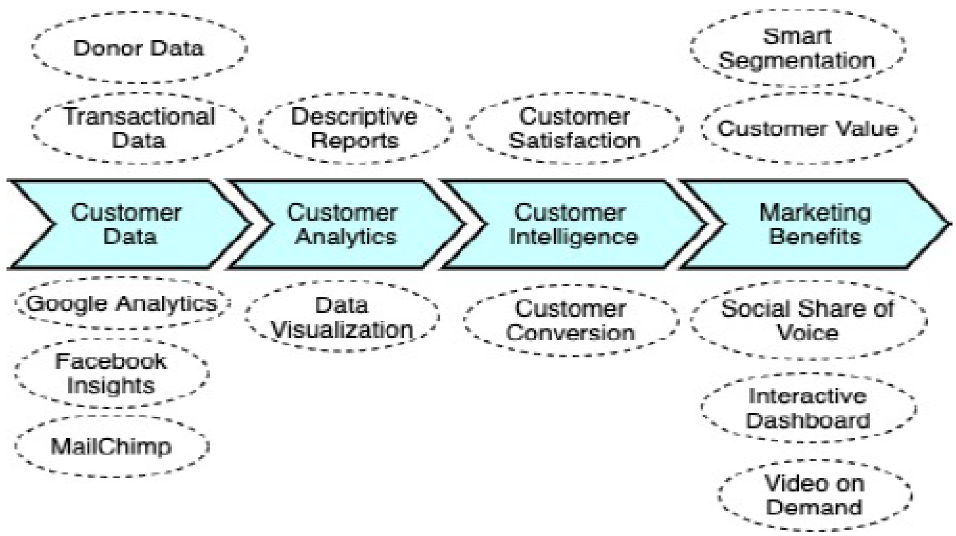
Figure 5.2
Alpha word cloud of top 100 words

Source: NVivo

5.1.1.2 Alpha case analysis

This section continues to analyze these above codes in detail with relevance to the constructs of the CIMB model (Figure 5.3). As customer data and customer analytics are interrelated, these two constructs are discussed together. Then the section takes a close analysis of customer intelligence and marketing benefits.

Figure 5.3
Findings from the case of Alpha



Source: Dam (2021)

As revealed by the managers, Alpha acquires different types of data, including transactional data of donors, donors, and other data from Facebook and Google Analytics. Transactional data of donors contain data on *order_number, order item, types, account, genders, state, country, zip code, subscription, event_name, price_with_taxes, date, sales_mode, and ticket_type*. Donor data contain data on account number, funding, date, amount, payment mode, city, province, postal code, and subscription. Through Google Analytics[6] and Facebook Insights[7], Alpha can acquire relevant data in standard formats. Alpha heavily relied on reports of Google Analytics to analyze traffic sources of their website. Google Analytics has become a useful tool to determine if the promotional campaigns are effective through the breakdown of traffic sources to the website. Accordingly, Alpha adjusted its marketing strategies. As the Sales and Customer Service Manager indicated, the most driving traffic of the site of Alpha came from sites of museums. Moreover, the managers of Alpha counted on analysis tools in MailChimp, a marketing automation platform and

[6] https://analytics.google.com/analytics/web/
[7] https://www.facebook.com/

email marketing service, so that they could see the most clicked links to improve promotional campaigns. However, the managers of Alpha expressed an interest in integrating data from different sources to see the consistency of extracted information or insights. From the management perspective, directors also emphasized the importance of data visualization to support the decision-making process. In this regard, the manager of Alpha mentioned that:

> *MailChimp uh - we had left for a while, but we came back with MailChimp - that there are analysis tools directly in MailChimp so that we can see what the links are, which are the most efficient, and then let's put that we made changes in the past.*

Regarding customer intelligence, the Director of Communications and Marketing attempted to collect customer satisfaction to improve the quality of services. However, it was challenging as the acquired data of each service were not equal. However, the directors thought that it was not necessary to measure how people reacted to videos or messages on the Facebook page of Alpha. Instead, the theatre wanted to know the most efficient channel to promote marketing campaigns. According to the director, the ultimate application of customer intelligence at Alpha was to convert users into customers. Currently, a significant proportion of sales conversion comes from newsletters. For the future campaign, the theatre aims at improving sales conversion at other channels.

Alpha aimed at leveraging the value of customer intelligence for long-term strategies instead of just focusing on the current situation of the COVID-19 pandemic. Similar to other cultural organizations, Alpha suffered from a loss of income and reimbursement for customers who already purchased the tickets. Alpha made a strong attempt to minimize costs because of the social lockdown. In the context of the COVID-19 pandemic, the theatre recognized the significance of show creativity and inventiveness as performances become rare. To deal with the pandemic, Alpha has technologically upgraded and created six labs to accelerate live productions and to produce high-quality recordings on new broadcasting platforms. As a result, about 2013 purchases of video on demand were made from 2020 to 2021. Among the collaborative initiatives that emerged during the 2020-2021 season, the Alpha team piloted the Webcasting Toolkit project for the Associated Theaters (TAI) group. In addition to the development of a video-on-demand module that any theater can now use, the project makes it possible to document this new practice, for the benefit of the entire performing arts domain.

The Director of Communications and Marketing desired to measure customer value through the reflection of the total value of the amount spent, the frequency, and the recency of purchases. According to the Director, recency, frequency, and monetary value (RFM) were the most precise indicators to measure customer engagement compared to the number of likes and shares on social media. However, it was also significant to make use of the network of customers on social media through the sharing activity. The Director emphasized the importance of social shares of voice in spreading the publications or postings of Alpha on social networks. Interestingly, the managers of Alpha showed a great interest in an interactive dashboard that could integrate data from different sources to promote the decision-making process. The interactive dashboard should allow the managers to inject new data at regular intervals instead of relying on the support of IT technicians. Therefore, the managers would be able to draw better data-driven decisions through the analysis of the latest and more diverse data. Furthermore, to highlight the benefits of customer intelligence for marketing, the managers of Alpha mentioned the need to identify new segmentation criteria. Traditionally, marketers have relied on social and demographic criteria such as age, sex, income, etc. for segmentation. Such segmentation criteria have become obsolete; consequently, the managers of Alpha are searching for smarter criteria for customer segmentation with the support of customer intelligence. Instead of targeting the segment of theatre enthusiasts, Alpha also aimed at the potential segment of culture omnivores whose consumption tastes include various cultural offerings. In fact, people with higher levels of income and education tend to belong to the segment of culture omnivores as they have more diverse cultural tastes with a greater volume of consumption. To illustrate, the director of Alpha revealed that:

> *Smarter criteria for segmentation rather than age, sex, ... This segment is passionate about the theater and other cultural offerings, more like an omnivore of culture. Therefore, the promotion of theatre shows can reach both theater enthusiasts and omnivores. This is what gives us good clues to expand our market compared to just focusing on theater enthusiasts.*

5.1.2 The intra-case analysis of Beta

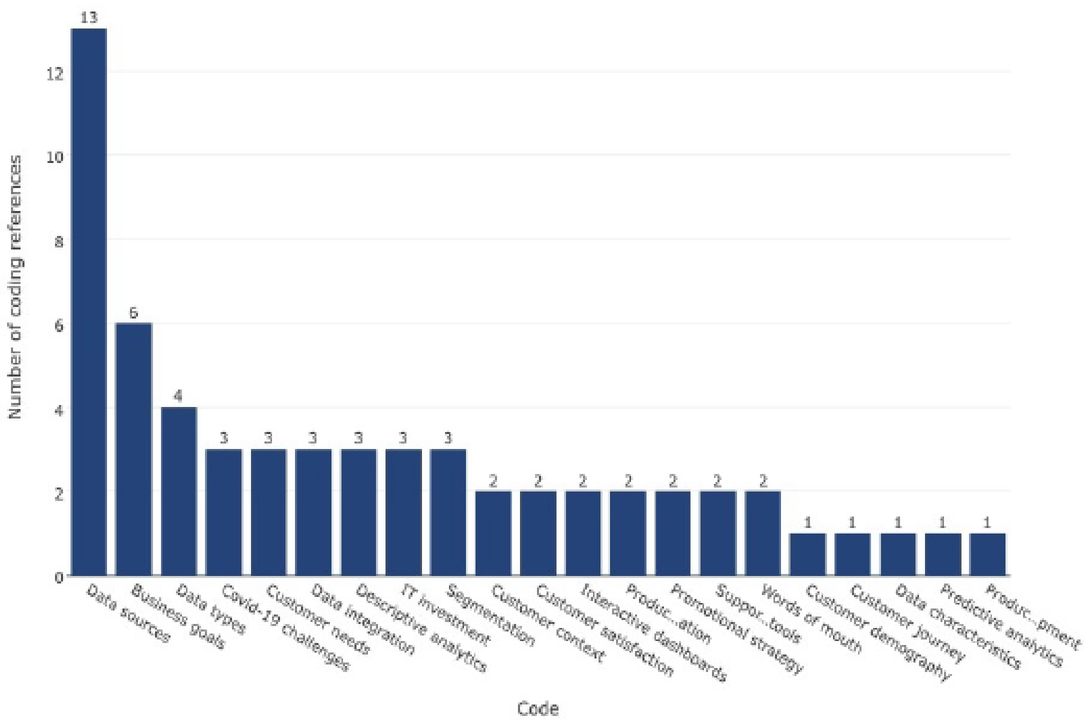
The section presents the case description and analysis of Beta. The case description relies on the thematic analysis to present statistics relating to the codes, top coding references, and most frequent words based on the interview data. On the flip side, the case analysis aims at interpreting codes related to the constructs of the CIMB model.

5.1.2.1 Beta case description

In this section, the thematic analysis is applied to define codes, top coding references, and most frequent words to provide an overview of the case of Beta.

In total, 22 codes with 113 coding references are identified from the interview data of Beta which are visualized in Figure 5.4. Among all codes, the most frequent coding references belong to "data sources", "business goals", "data types", "customer need", and "data integration". As the most frequent code, "data sources" indicate the vast amount of data that Beta possesses. Along with this line, the top coding reference points out that the managers and directors of Beta take into consideration "business goals" and "customer needs" in adopting customer intelligence. They also emphasize the importance of "data integration" to strengthen data-driven decisions. The following part of the document will further investigate these codes regarding the constructs of the CIMB model.

Figure 5.4
Most frequent coding references of Beta



Source: NVivo

The top 100 words extracted from the interview data for the Beta Case are visualized in Figure 5.5. The most frequent words are “data” (118 counts, or 1.16%) followed by “customer” (90 counts, or 0.88%), “museum” (61 counts, or 0.60%), “information” (48 counts, or 0.47%), and “products” (37 counts, or 0.36%). This gives prominence to the significance of "data" and "information" from "customers" for the "products" of the "museum". It is also crucial to explore other most repeated words such as "analytics", "development", "schools", "partners", "services", "decisions", and so on to catch the attention of the managers and directors of Beta for long-term strategies. In this light, it can be inferred that the managers and directors of Beta aim at applying "analytics" for "service development" and "decisions". They also yearn for cooperating with “schools” as potential "partners". The Appendix G of this document provides more detail on the number of counts and weighted percentage of each word.

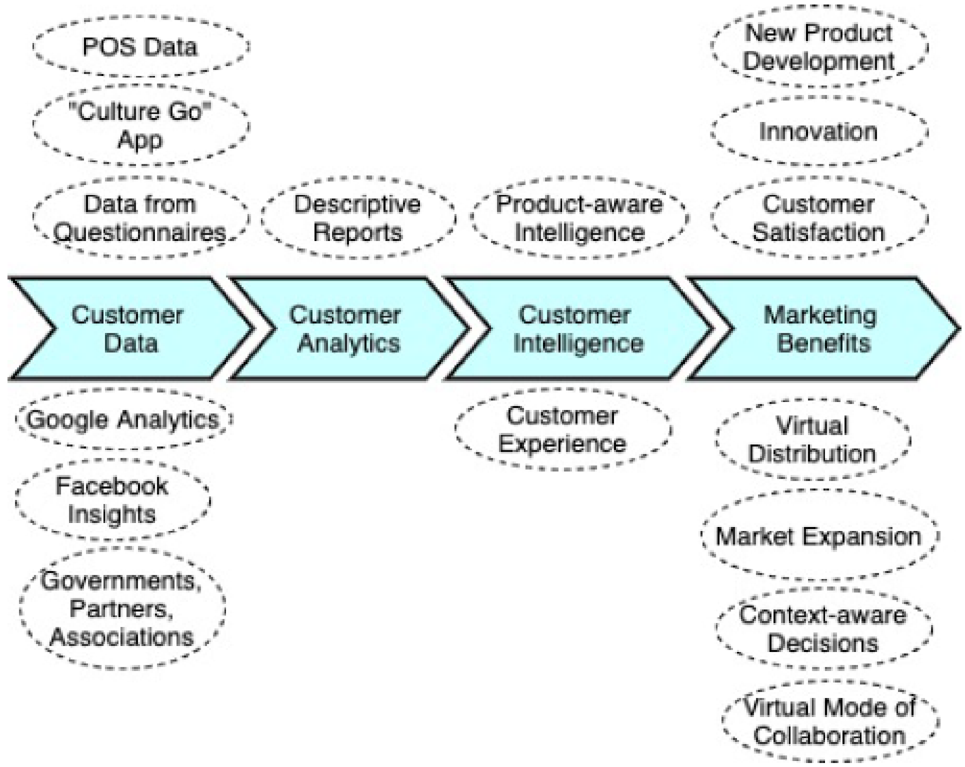
Figure 5.5
Beta word cloud of top 100 words

Source: NVivo

5.1.2.2 Beta case analysis

In this section, the above codes are analyzed in detail with respect to the constructs of the CIMB model (Figure 5.6). Since customer data and customer analytics are interrelated, these two constructs are discussed together. This is followed by a detailed analysis of customer intelligence and marketing benefits.

Figure 5.6
Findings from the case of Beta



Source: Dam (2021)

Beta has access to diverse sources such as Point of Sales data (POS), Google Analytics, the "Culture Go" Application, questionnaires, Facebook Insights, and other sources of the government and cultural associations. Furthermore, this cultural organization has acquired data related to emails of cultural consumers from its partners to promote marketing campaigns through the newsletter platform of MailChimp. To collect customers' feedback on products/services, Beta often relies on questionnaires as the main tool to compare with other products/services of museums in Québec. Even though Beta has diverse access to data sources, they did not know what to do with these data as the communications and marketing manager said. In particular, the communications and marketing manager indicated that she could extract data from Facebook or Google Analytics to see who went to the site and who went to the Facebook page; however, she was not able to integrate data systematically. Therefore, she was not sure who visited the Facebook page or website and how to find them after that. She emphasized the need for such a type of customer intelligence, which connects to the customer experience intelligence mentioned in this study. To take advantage of customer intelligence beyond descriptive reports, Beta tried to hire a firm to work with diverse data sources; however, it took time to see the result. Consequently, the director expressed a strong need for a dashboard that can integrate and analyze data on a monthly basis. The concern for data integration to optimize data-driven is quoted as follows.

> *How can we also optimize all the data that we can have via Google Analytics so that we could have a connection with the behavior of the visitors from Facebook Insights and Google Analytics? Is there a way to go and see who went to our Facebook page, who went to our site, and also to follow them through Google Analytics? Yes, there are data that I can extract from all that, there, but I do not do it systematically, because I do not have the time. I do it once in a while, but not systematically.*

The manager and director of Beta showed an interest in customer experience intelligence and product-aware intelligence. In fact, it is easy to see who your customers are with the support of Google Analytics and Facebook Insights, but it is challenging to follow up with them. As such, customer experience intelligence emerges as a means to convert users to customers and involves in the process of customer engagement. On the flip side, Beta had a concern about product-aware intelligence in understanding customer satisfaction with the cultural products/services. Accordingly, this organization conducted questionnaires to see whether visitors of "on the open house" (e.g., school students) or customers of room rentals were satisfied with offered services. Considering the nature of the museum domain, managers of Beta were also interested in contextual data of customers to optimize and keep track of services. In the museum domain, cultural consumers depend on contextual data related to weather, school year, and major holidays to plan their trips. For example, if it is minus 15ºC, it is minus 15% of the number of visitors. Being aware of contextual data, Beta has adjusted its promotional strategies. In January when the number of visitors is low, the organization offered a 20% discount to attract customers.

Beta expressed an interest in marketing benefits for the current situation and long-term strategies. In dealing with the COVID-19 pandemic, Beta has promoted the creation and distribution of virtual access content. Certain exhibitions and activities are offered in the virtual mode. The virtual offerings have opened new markets for Beta in reaching new customers who could not make long-distance travels to visit the museum. Beta had reservations from schools in British Columbia and elementary schools of Bas-du-Fleuve that are new customers in the COVID-19 pandemic. As stated by the director of Beta:

> *Our customer priority is indeed the family, but schools are also potential customers. This segment is important to us since this is often where we will sow the seed of love of culture, the discovery of culture. Thus, it is important for us to have a program that offers activities from preschool to university.*

Interestingly, Beta made use of the lockdown period for innovative product/service development. In fact, this organization has collaborated with Rhum n Code, a company of the DigiHub of Shawinigan, to develop the Muséolab in promoting the virtual mode of collaboration with partners. The Muséolab gave birth to the application called "Culture Go" which allows the museum to transfer all exhibition content to the digital platform. Customers only need to scan their QR (quick response) codes to access virtual exhibitions.

To attain marketing benefits, the manager and director of Beta aim at applying customer intelligence to various marketing decisions. Firstly, customer intelligence is expected to improve context-aware decisions concerning the influence of weather, holidays, and timings on the decision-making process. Secondly, managers of Beta also expect to make use of customer intelligence in product/service development to satisfy the needs of customers. This would enhance the marketing and financial performance of this cultural organization. Finally, Beta is in need of a decision support system or tool (e.g., a dashboard) to improve marketing decisions. As the managers are overwhelmed with customer data, they find it challenging to integrate all the data sources to produce reliable data-driven decisions.

5.1.3 Inter-case analysis of Alpha and Beta

This part continues with the inter-case analysis to reveal the interrelationship between the cases (Baxter & Jack, 2008; Yin, 2015). As discussed in Chapter 4, the thesis adopts both case-oriented and variable-oriented strategies to explore the interrelationship among cases (Della Porta, 2008).

Figure 5.7
Heatmap of codes of Alpha and Beta

Codes	Alpha Case	Beta Case	Total
Descriptive analytics	5	3	8
Experts	3	0	3
Predictive analytics	0	1	1
Support services or tools	6	2	8
Visualization	2	0	2
Customer context	0	2	2
Data characteristics	0	1	1
Data integration	3	3	6
Data sources	8	13	21
Data types	3	4	7
Data updates	1	0	1
Customer conversion	11	0	11
Customer demography	2	1	3
Customer engagement	7	0	7
Customer experience	3	0	3
Customer satisfaction	2	2	4
Product and ser...e development	0	1	1
Product and service innovation	0	2	2
Customer journey	1	1	2
Customer preferences	3	0	3
Customer value	3	0	3
Interactive dashboards	1	2	3
Segmentation	6	3	9
Business goals	0	6	6
Covid-19 challenges	3	3	6
Customer needs	0	3	3
IT investment	0	3	3
Promotional strategy	2	2	4
Words of mouth	0	2	2
Total	**75**	**60**	**135**

Source: NVivo

5.1.3.1 Case-oriented strategy

The case-oriented strategy aims at clarifying the similarities and differences among cases (Della Porta, 2008). To check the correlation of codes across the cases Alpha and

Beta, a cross-tabulation is created through the support of the software Nvivo. Code comparisons of these cases can be found in Appendix H of the document. Figure 5.7 demonstrates the heatmap of codes with coding references extracted from the cases. The colors of the codes represent their importance with variations from light red to dark red. Light red is the least connected whereas dark red indicates the most popular codes.

Even though Alpha and Beta operate in the same cultural market, they are not direct competitors, and their products are quite distinct: theatre shows for Alpha whereas exhibitions and room rentals for Beta. In fact, there is an interrelationship between the consumption of cultural events of Alpha and Beta. Cultural consumers tend to consume theatre shows after the museum activity. As mentioned by the director of Alpha, a significant number of traffic sources come from the websites of museums. Furthermore, the interview results reveal that these organizations have acquired different types of customer data from transactions, Google Analytics, Facebook Insights, POS systems, application, etc. However, transforming customer data into customer intelligence to create value is a challenging task. Firstly, cultural organizations find it defiant to pull data from different sources altogether to optimize data-driven decisions. Cultural managers believe that they cannot put trust in the analysis result of a single source of data. Secondly, managers and directors of Alpha and Beta expressed the importance of analyzing recent data to support the decision-making process. As a matter of fact, cultural managers rely on IT technicians to combine data from different sources. This process is time-consuming; thus, managers are not able to work directly with the data and make decisions upon the "real-time" property of data. The recency characteristic of data is important in improving the quality of data-driven decisions. This stimulates the need for interactive dashboards or customer intelligence systems that enable managers to perform different tasks from importing, exporting, cleaning, and integrating data to generating and visualizing customer intelligence for the decision-making process. Finally, managers and directors of these organizations shared a common view on applying customer intelligence for marketing benefits. Alpha is interested in marketing decisions related to smart segmentation, customer value, the social shares of voice, and interactive dashboard. Beta aims at applying customer intelligence for innovation, financial performance, context-aware decisions, and decision support systems.

The Alpha Case highlights the significance of customer conversion (coding reference = 11), customer engagement (coding reference = 7), segmentation (coding reference = 6) with the support of services or tools (coding reference = 6) for analytics (coding reference = 5). In other words, Alpha focuses on customer experience intelligence and customer DNA intelligence. On the flip side, Beta recognizes the diversity and importance of "data sources" which is the code in the darkest red with the coding reference equal to 13. However, they are somehow confused in defining the right type of customer intelligence. This is one of the significant challenges that most SMEs/SMOs are facing. A positive signal is that Beta shows their interest in learning about customer segmentation (coding reference = 3) and willingness to invest in information technology to integrate data (coding reference = 3) from various sources.

5.1.3.2 Variable-oriented strategy

The variable-oriented strategy focuses on the constructs of the conceptual model (Della Porta, 2008). Therefore, this section will compare the constructs of customer data, customer analytics, customer intelligence, and marketing benefits across the cases.

The codes “data sources” and “data types” are one of the most frequent codes among the cases. Another point to ponder is that Beta accentuates the significance of contextual data due to the nature of its cultural products and services. However, data integration and analytics are challenges for all of them. To exploit these data, Alpha emphasizes the importance of experts and supporting services or tools for analytics compared to.

Customer DNA intelligence is the common denominator for Alpha and Beta. These cultural organizations spotlight the need for customer intelligence for customer segmentation and profiling. Alpha and Beta also share a common view on product-aware intelligence to improve customer satisfaction with provided products and services. Finally, applying customer value seems to be a challenging task to Alpha and Beta. Even though Alpha yearns for measuring customer value through the recency, frequency, and monetary of customers, this organization is not ready and needs more time and capability to make it happen.

As Alpha and Beta put trust in customer-DNA intelligence, they all acknowledge the significance of customer segments to improve marketing strategies. Other marketing benefits that catch the most attention of these organizations are product/service development, product/service innovation, and customer preferences. Finally, Alpha and Beta indicate the significance of interactive dashboards to achieve marketing benefits. These dashboards will solve the challenge of data integration mentioned by these cultural organizations. Furthermore, interactive dashboards can help managers of Alpha and Beta overcome the obstacle of customer analytics to directly interact with data and produce insightful outcomes.

5.2 DISCUSSIONS OF THE MULTIPLE CASE STUDY

Based on the analysis of interview data, this section continues to discuss the current, emerging, and future practices of Alpha and Beta. The three stages of practice can serve as a roadmap for customer intelligence adoption for marketing benefits. The current practice is already analyzed in detail in the previous part. Therefore, this part highlights the emerging and future practices. The emerging practice presents the near future actions that Alpha and Beta can take into consideration, whereas the future practice focuses on long-term strategies. To verify the applicability of the CIMB model, the section also demonstrates the interactive dashboards for these cultural organizations.

5.2.1 Discussion of the Alpha case

This section discusses the current, emerging, and future practices of Alpha based on the results of data analysis in the previous part of this chapter. Subsequently, a demonstration of the interactive dashboard for Alpha is presented to add value to the applicability of the CIMB model. The dashboard is developed based on data provided by Alpha with an aim to support marketing decisions.

5.2.1.1 The current, emerging, and future practices of Alpha

Table 5.1 presents the current, emerging, and future practices of Alpha with relevance to customer data, customer analytics, customer intelligence, and marketing benefits. The current practice of Alpha which is present in the previous part reveals that this organization is in the early stage of customer intelligence adoption. This part further discusses the action plans for the next stage (emerging practice) and the long-term stage (future practice).

Table 5.1
The current, emerging, and future practices of Alpha

	Current Practice	**Emerging Practice**	**Future Practice**
Customer Data	- Donor data, transactional data, Google Analytics, Facebook Insights, MailChimp - Some data are unstructured. - Data are scattered, and out of context.	- Integrating different sources of data - Standardizing the structure of data	- Acquiring real-time data - Recognizing data in a context
Customer Analytics	- Descriptive reports - Data visualization	- Continuing with diagnostic analytics - Applying software supporting analytics to visualize data - Implement association and clustering techniques for segmentation of online users	- Adopting big data analytics - Natural language processing and deep learning to understand the contexts of customers
Customer Intelligence	- Customer satisfaction - Customer conversion	- Applying product-aware intelligence for product/service development and innovation - Learn customer experience intelligence through their interaction on the website	- Proposing product/service innovation by mining customer content on digital platforms - Matching theatre events with the context of customers (e.g.: time, location, etc.) - Applying CI to directly interact with customers on the website

	Current Practice	Emerging Practice	Future Practice
Marketing Benefits	- Market expansion - Measuring customer value by recency, frequency, and monetary value	- Smart criteria for segmentation, targeting, and positioning - Exploiting the social value of customers on digital platforms	- CI-based optimization of segmentation, targeting, and positioning - Co-creating cognitive value of customers (knowledge, skills, and experience)

Source: Dam (2021)

With regards to the emerging practice, Alpha can start with integrating different sources of data and standardizing the structure of internal data. Diagnostic analytics is the emerging practice for customer intelligence. To deal with the limited analytic capability, managers of Alpha can consider the application of software supporting analytics to visualize data and support marketing decisions. An option that Alpha can try is Power BI[8], a business data analytics software by Microsoft that produces business intelligence through the support of an interactive dashboard. Regarding customer intelligence, Alpha can apply conjoint analysis for product/service development and innovation (Tasic et al., 2020; Werner et al., 2020). As the managers of Alpha aim at improving customer experience intelligence for better customer conversion, they can adopt association and clustering techniques to segment online users and understand their behaviors through online metrics such as exit rate, average session duration, conversion rate, views, etc. Finally, the emerging practice of marketing benefits gives prominence to smarter criteria for the STP (segmentation, targeting, and positioning) process. Based on the association and clustering techniques of behaviors of online users, Alpha can improve the traditional STP process. For example, some enterprises rely on the churn rate and acquisition rate as criteria for segmentation (Huang & Rust, 2021). With the support of customer experience intelligence, Alpha is likely to achieve

[8] https://powerbi.microsoft.com/

this marketing benefit. Another emerging practice of marketing benefit is to exploit the social value of customers on digital platforms by taking advantage of their social influence through social status and networks.

Alpha can consider recognizing data in a context. It is also significant to take into account the real-time attribute of data. As a result, big data analytics can be adopted to automatically propose product/service innovation by mining customer content on digital platforms. Moreover, contextual data also leverage the value to another level by matching the theatre events of Alpha with relevant contexts of customers (e.g.: time, location, festivals, etc.). The future practice for Alpha also lays out the application of customer intelligence towards a chatbot or an insight search bar to directly interact with customers on the website.

5.2.1.2 Demonstration of the interactive dashboard for Alpha

This section of the thesis presents a decision-supporting tool for Alpha, hereafter called DST-CO. DST-CO is developed based on Power BI, a business analytics service by Microsoft that aims at providing interactive visualizations and business intelligence capabilities with an interface simple enough for end-users. Through the support of Power BI, users can easily create their reports and dashboards. DST-CO takes into consideration the availability of data provided by Alpha organization in Montreal, Quebec. Furthermore, key performance indicators (KPIs) that are visualized in DST-CO are also tailored to the nature of the decision-making process as well as the analytic capabilities of typical organizations in the cultural sector. The subsequent parts clarify the available data, types of analytics, and interface along with the marketing benefits of DST-CO.

DST-CO is developed based on three types of data that are provided by a cultural organization in Montreal, Quebec including transactional data of donors, donors, and Facebook. *Transactional data of donors* contain data on order_number, order item, types, account, genders, state, country, zip code, subscription, event_name, price_with_taxes, date, sales_mode, and ticket_type. Transactional data are from 2018 to 2019. *Donor data* contain data on account number, funding, date, amount, payment mode, city, province, postal code, and subscription. These data are from January 2018 to September 2018. *Facebook data* are obtained from Facebook insights. Facebook data include lifetime total likes, reach, impression, number of positive and negative feedback, demographic info, and so on. These data are from January 2019 to December 2020.

Based on the nature of available data, DST-CO focuses on two types of analytics: descriptive analytics and predictive analytics. Descriptive analytics and predictive analytics cover different techniques, including classification, prediction, statistics, sequence discovery, and clustering (Baesens et al., 2016; Chen et al., 2012; McAfee et al., 2012). Based on these analytic techniques, Table 5.2 summarizes techniques associated with KPIs from DST-CO.

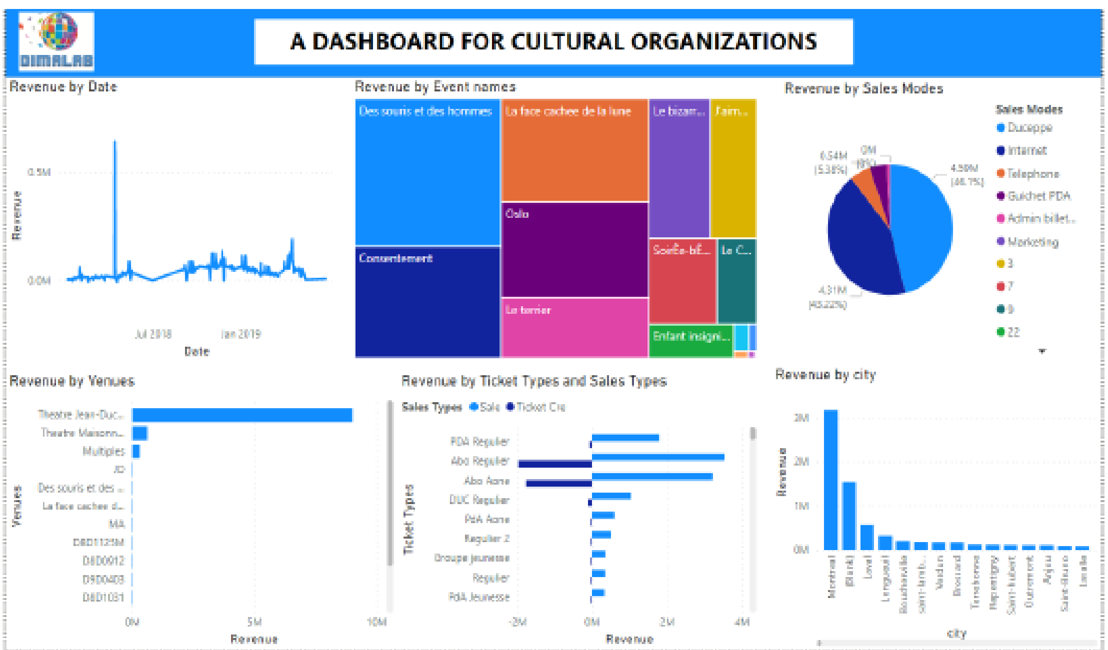
Table 5.2
Analytic techniques associated with KPIs from DST-CO

KPIs	**Analytics**	**Specific techniques**
Revenue over a period	Descriptive analytics and predictive analytics	Prediction
Revenue by venues	Descriptive analytics	Classification
Revenue by events	Descriptive analytics	Classification
Revenue by ticket types and sales	Descriptive analytics	Classification
Revenue by sales modes	Descriptive analytics	Classification
Revenue by cities	Descriptive analytics	Classification
Funds by city	Descriptive analytics	Classification
Funds by month	Descriptive analytics	Classification
Account by subscription	Descriptive analytics	Clustering
Subscription by city	Descriptive analytics	Classification
Funds by company	Descriptive analytics	Classification
Lifetime total likes by dates	Predictive analytics	Prediction
Daily total reach by date	Predictive analytics	Prediction
Daily likes sources	Descriptive analytics	Statistics
Positive comments and negative comments by date	Descriptive analytics	Sequence discovery
Daily organic reach and daily paid reach by month	Descriptive analytics	Sequence discovery
Daily organic reach and daily paid reach by months	Descriptive analytics	Sequence discovery
Customer segment	Descriptive analytics	Clustering

Source: Dam (2021)

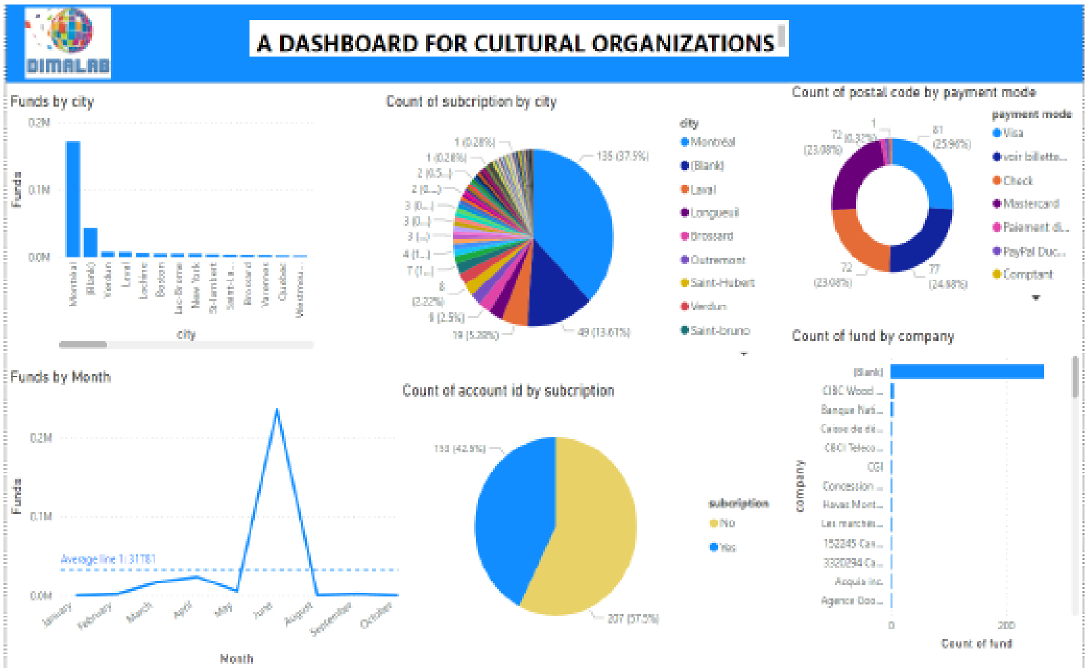
The interface of DST-CO demonstrates three dimensions, including Finance (Figure 5.8), Customers (Figure 5.9), and social media, particularly Facebook (Figure 5.10). Firstly, the finance dimension highlights the importance of the KPIs on revenue. Accordingly, revenues are grouped by event, venues, sales modes, ticket types, sale types, and city. The fluctuation of revenue is also explored from 2018 to 2019. The forecasting technique is also applied to predict the trend of revenue. Secondly, the customer dimension focuses on KPIs on funds from cultural donors. Funds are grouped by city, subscription, and company. The amount of funds received over a period is also visualized to show the trend. Lastly, due to the available data, DST-CO focuses on Facebook for the social media dimension. Among numerous KPIs from Facebook Insights, DST-CO keeps track of key metrics such as lifetime total likes, daily total reach, daily likes sources, customer segment, positive comments, negative comments, and so on. Compared to the dashboard of Facebook Insights, DST-CO stands out due to insights based on forecasting techniques. Accordingly, lifetime total life and daily total reach can be predicted in days, months, or quarters. DST-CO is also outperformed due to the combination of relevant KPIs to support the decision-making process. For example, daily organic reach and daily paid reach are plotted together to see the efficiency of marketing plans.

Figure 5.8
The interface of the finance dimension



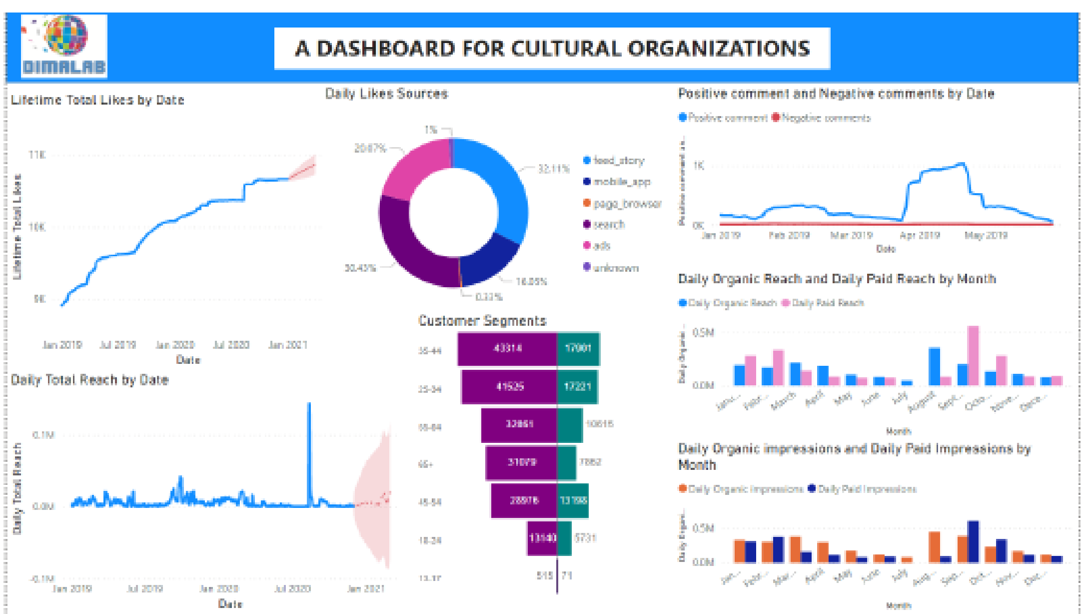
Source: Dam (2021)

Figure 5.9
The interface of the customer dimension



Source: Dam (2021)

Figure 5.10
The interface of the social media (Facebook) dimension



Source: Dam (2021)

To highlight the marketing benefits of the CIMB model for the DST-CO dashboard, Table 5.3 provides a summary of marketing benefits. Subsequently, KPIs from DST-CO are also classified based on these marketing benefits. Table 5.4 presents the classification of KPIs from DST-CO with relevance to types of customer intelligence and marketing benefits.

Table 5.3
Types of marketing benefits associated with customer intelligence

Types of Customer Intelligence	**Marketing Benefits**
1. Product-aware Intelligence.	1.1 Product/service development 1.2 Product/service innovation 1.3 Customer preference
2. Customer DNA Intelligence.	2.1 Customer segmentation 2.2 Customer profiling (targeting)
3. Customer Experience Intelligence	3.1 Customer journey 3.2 Customer experience 3.3 Customer recommendation
4. Customer Value Intelligence	4.1 Customer value 4.2 Customer lifetime value 4.3 Customer co-creation

Source: Adapted from Chaffey and Ellis-Chadwick (2019)

Table 5.4
Classification of KPIs and marketing benefits

KPIs	**Marketing Benefits**	**Dimensions**
Positive comments and negative comments by date	3.2 Customer experience	Customer
Daily organic reach and daily paid reach by months	3.1 Customer journey	Social media
Daily organic reach and daily paid reach by months	3.1 Customer journey	Social media
Customer segment	2.1 Customer segmentation	Customer
Daily total reach by date	3.1 Customer journey	Social media
Lifetime total likes by dates	4.2 Customer lifetime value	Customer
Daily likes sources	3.1 Customer journey	Social media
Revenue over a period	4.1 Customer value	Finance
Revenue by venues	4.1 Customer value	Finance
Revenue by events	4.1 Customer value	Finance

KPIs	Marketing Benefits	Dimensions
Revenue by ticket types and sales	4.1 Customer value	Finance
Revenue by sales modes	4.1 Customer value	Finance
Revenue by cities	4.1 Customer value	Finance
Fund by city	2.2 Customer profiling (targeting)	Finance
Fund by month	2.2 Customer profiling (targeting)	Finance
Account by subscription	2.2 Customer profiling (targeting)	Customer
Subscription by city	2.2 Customer profiling (targeting)	Customer
Funds by company	2.2 Customer profiling (targeting)	Finance

Source: Adapted from Chaffey and Ellis-Chadwick (2019)

5.2.2 Discussion of the Beta case

The analysis of the interview data of Beta reveals the current practices and infers the emerging and future practices. Developed upon data provided by Beta, the interactive dashboard is also presented to verify the applicability of the CIMB model.

5.2.2.1 The current, emerging, and future practices of Beta

The current, emerging, and future practices of Beta with relevance to customer data, customer analytics, customer intelligence, and marketing benefits are summarized in Table 5.5. As the current practice is discussed in the analysis part, this section focuses on the emerging and future practices.

Similar to Alpha, Beta is in the early stage of customer intelligence adoption. For the emerging practice, Beta can start with integrating data from various sources to leverage the reliability of data-driven decisions. As stated by the manager of Beta, the consumption nature of services offered by this organization depends on contextual data such as weather, school year, and major holidays. Therefore, it is necessary to collect contextual data to improve marketing performance. Also, managers of Beta should consider collecting and analyzing customer feedback from the "Culture Go" app or the website to learn more about customer satisfaction. The emerging practice of customer analytics may involve the adoption of an interactive dashboard to integrate, analyze, and visualize data. Furthermore, the managers of Beta can consider analyzing the sentiments of users on social media. This helps Beta better understand and predict their behaviors in different contexts with relevance to the purchase and consumption of museum events. The emerging practice for customer intelligence is to rely on product-aware intelligence to recommend relevant services and generate personalized post-visit souvenirs and online visualization according to customer experience with Beta. Beta can also take advantage of customer experience intelligence to personalize the museum experience by engaging visitors with the right information at the right time and with the right types of interactions during their museum experience. Users are free to shape their personal experiences by selecting the content or stories they are interested in. Based on historical data, customer experience intelligence can recommend activities for their next visits. Therefore, marketing benefits for the emerging practice give prominence to service recommendations based on the contexts and preferences of customers. Accordingly, Beta can develop customer profiles to keep track of customers, especially top profitable customers.

Table 5.5
The current, emerging, and future practices of Beta

	Current Practice	**Emerging Practice**	**Future Practice**
Customer Data	- POS data, "Culture Go" App, questionnaires, Google Analytics, Facebook Insights, and other sources from governments, partners, and associations.	- Integrating data sources - Collecting contextual data (weather, school year, and major holidays) from open sources - Collecting customer feedback on the "Culture Go" app	- Real-time data - Big data
Customer Analytics	- Descriptive analytics - Support of MailChimp	- An interactive dashboard to analyze and visualize data - Analyzing sentiments of users on social media - Predicting customer behaviors in different contexts	- Prescriptive and cognitive analytics
Customer Intelligence	- Product-aware intelligence improves customer satisfaction - Customer experience intelligence engages customers	- Product-aware intelligence recommends relevant services and generates personalized post-visit souvenirs and online visualizations according to what visitors have experienced - Customer experience personalizes museum experience	- Product-aware intelligence matches personalized services based on emotions, contexts, preferences of customers - Focusing on other types of CI

	Current Practice	Emerging Practice	Future Practice
Marketing Benefits	- Product/service development and development - Customer satisfaction - Market expansion - Virtual distribution - Virtual mode of collaboration	- Recommending services based on context and preferences of customers - Developing customer profiles	- Recommending services based on emotions - Context-aware customer intelligence system - Training bots to have onsite communication with customers - Real-time conversation with customers

Source: Dam (2021)

The future practice of Beta should take into account real-time data and big data through the support of prescriptive and cognitive analytics to leverage the value creation of customer intelligence. Prescriptive analytics can optimize and simulate marketing decisions whereas cognitive analytics can automatically learn from customer interactions and propose relevant action plans. At a higher level, product-aware intelligence can match personalized services based on the emotions, contexts, and preferences of customers. In this stage, Beta can also focus on other types of customer intelligence to achieve different marketing benefits. For example, product-aware intelligence can learn the emotions and sentiments of users on social media; thus, it can recommend relevant services based on that. The literature points out that people tend to experience museum activity when they are depressed. Museum visits are considered a therapy to help them feel happier. Therefore, learning the emotions of users and recommending relevant services would result in fruitful outcomes. In the future, Beta can give rise to a context-aware customer intelligence system to achieve these marketing benefits. Furthermore, it is important to have real-time conversations with customers for better engagement. Therefore, the future practice for marketing benefits would involve training a chatbot to communicate on-site with customers.

5.2.2.2 Demonstration of the interactive dashboard for Beta

This section aims at clarifying the data and analytics of the interactive dashboard for Beta. Then a detailed discussion is presented to enlighten how the interactive dashboard creates marketing benefits.

The dashboard is developed based on three types of data from transactions, Google Analytics, and Facebook of Beta. Based on the nature of available data, the dashboard focuses on data mining methods, including classification, association, clustering, and prediction. Table 5.6 presents different types of KPIs corresponding with business questions, data types, and data mining methods. Compared to the dashboard for Alpha, the dashboard for Beta further leverages the value of customer intelligence through business questions for marketing benefits. Furthermore, the visualization of customer intelligence towards graphs, tables, and charts facilitates the decision-making process of business users. Based on the availability of data, the dashboard for Beta covers three types of customer intelligence, including product-aware intelligence, customer DNA intelligence, and customer experience.

Table 5.6
Descriptions of the dashboard for Beta

CI	**KPIs**	**Business Questions**	**Data Types**	**Data Mining Method**
Product-aware Intelligence	Revenue by month	How well is revenue growing?	Transactional data	Classification
	Total revenue	What is total revenue?	Transactional data	Classification
	Top profitable events	What are the most profitable events?	Transactional data	Classification
	Top profitable events	What are the most popular events?	Transactional data	Classification
	Correlated events based on transactions	What events can be sold together?	Transactional data	Association

CI	KPIs	Business Questions	Data Types	Data Mining Method
	Correlated events based on customer behaviors	Customers who purchase this event are likely to purchase what?	Behavioral data	Association
Customer Experience Intelligence	Bounce rates over average session duration	How well does the website engage with online users?	Behavioral data	Association and Clustering
	Profiles of user clusters	What are the characteristics of online users?	Behavioral data	Clustering
	Coefficients of web metrics	How effective is the website?	Behavioral data	Association
	Top searches	What are the top searches on the website?	Behavioral data	Classification
	Most popular pages	What are the most popular pages?	Behavioral data	Classification
Customer DNA Intelligence	Customer sources	Where do customers come from?	Transactional data	Classification
	Customer profiles	What are the differences among customers from various sources?	Demographic data	Classification
	Customer attendance	How is customer attendance over years?	Demographic data	Classification
	Reach per day	How many customers does your Facebook page reach per day?	Behavioral data	Prediction
	Customer Sentiment	How do customers interact on Facebook?	Behavioral data	Classification
	Organic reach/ paid reach	How effective is our promotional campaign on Facebook?	Behavioral data	Classification

Source: Adapted from Chaffey and Ellis-Chadwick (2019)

Firstly, Figure 5.11 demonstrates the value creation of product-aware intelligence. As the data come from an organization in the cultural sector, cultural events are the key products. Product-aware intelligence allows business users to track revenue, the most profitable events, and the most popular events. Compared to other dashboards, product-aware intelligence makes a difference in recommending what events can be sold together based on transactional data. In addition, product-aware intelligence enables business users to be aware of customers who share similar purchasing behaviors. Therefore, managers of Beta can rely on product-aware intelligence to improve cross-selling strategies.

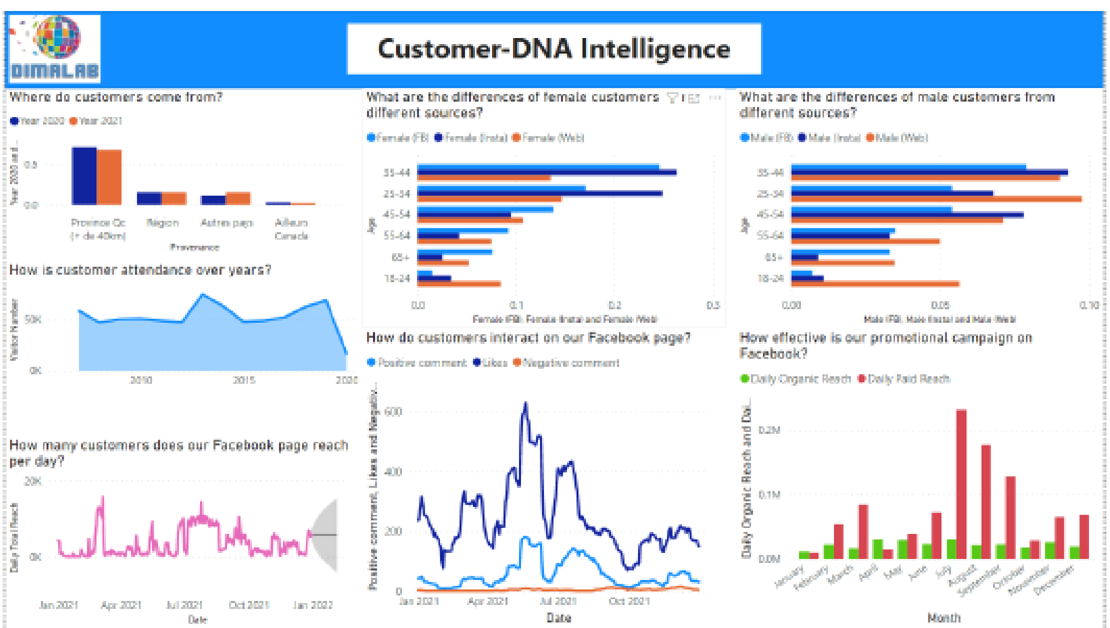
Secondly, Figure 5.12 visualizes KPIs related to customer DNA intelligence, which allows business users to be aware of where customers come from, their attendance over time, and the differences in customer demography among various sources such as websites, Facebook, and Instagram. The significance of the dashboard is that it integrates different data sources; therefore, customer DNA intelligence provides a multi-facet overview of customer demography. In addition, customer sentiments on Facebook through the comparison of positive and negative comments along with the number of likes help business users better understand their customers.

Lastly, Figure 5.13 shows KPIs related to customer experience intelligence on the website of Beta. Compared to Google Analytics, the approach of customer experience intelligence is different. Accordingly, customer experience intelligence relies on association and clustering methods to define different clusters of online users. To better understand the characteristics of each cluster, a description table is provided with metrics related to bounce rate, exit rate, number of users, page views, and conversion rate. The correlation matrix of these metrics is also provided for each cluster to help marketers understand the behaviors of online users. Finally, top searches and top pages are visualized to support marketing decisions.

Figure 5.11
Marketing benefits from product-aware intelligence for Beta

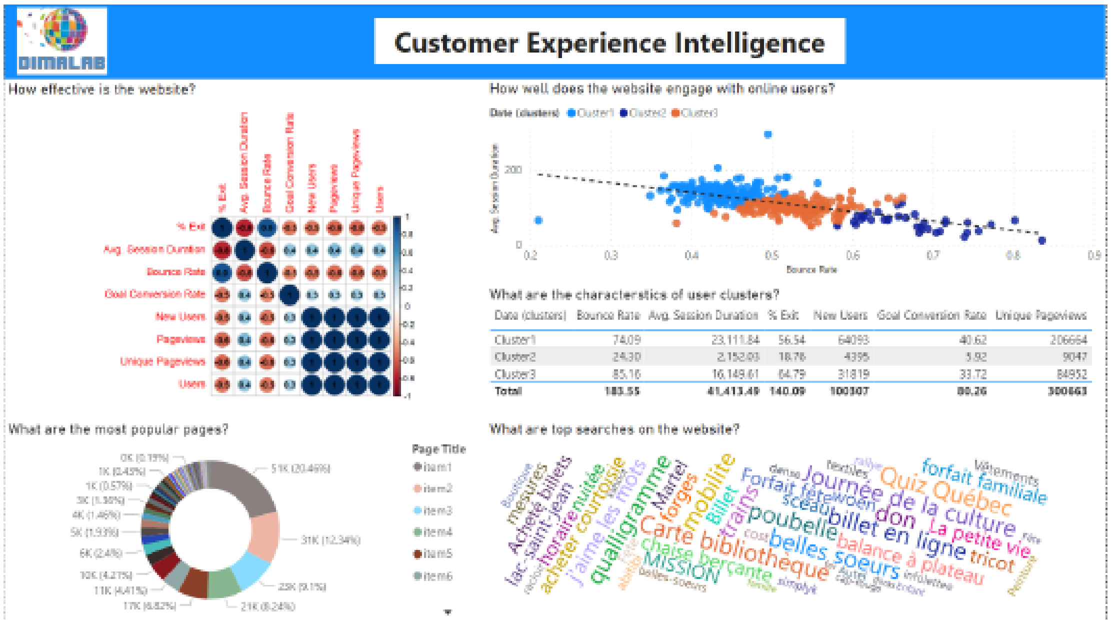
Source: Dam (2021)

Figure 5.12
Marketing benefits from customer DNA intelligence for Beta



Source: Dam (2021)

Figure 5.13
Marketing benefits from customer experience intelligence for Beta



Source: Dam (2021)

5.3 RECOMMENDATION

Based on the current, emerging, and future practices in the previous part of the chapter, this section proposes the maturity model of customer intelligence for marketing benefits. The maturity model aims at diagnosing the status-quo of enterprises with specific recommendations for the adoption of customer intelligence. In this light, the section presents the diagnostic tool and the maturity model of customer intelligence for marketing benefits.

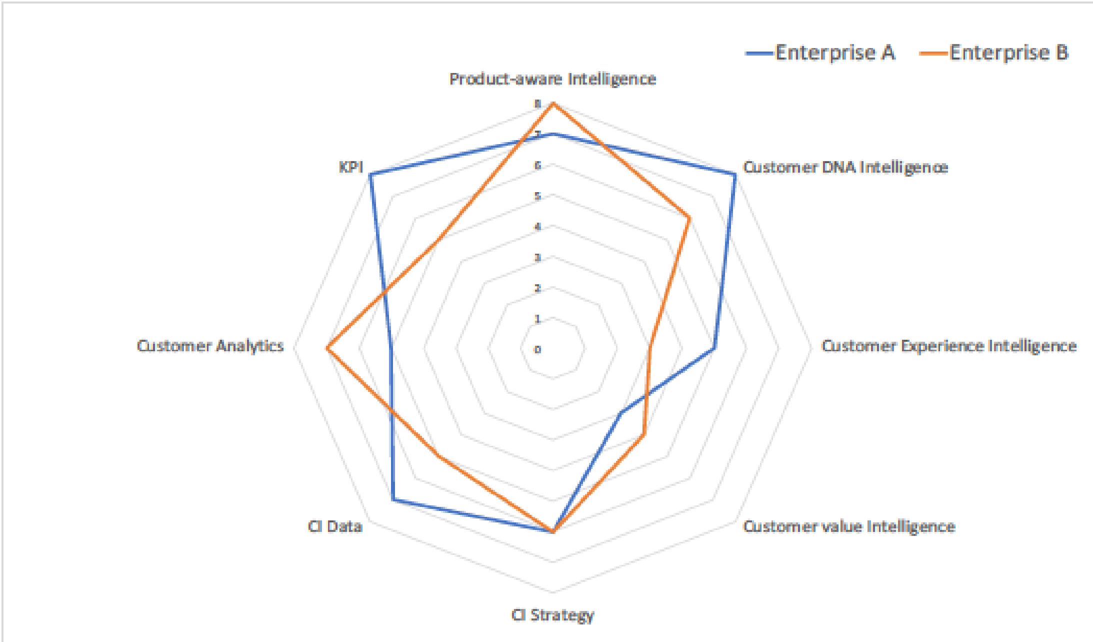
The maturity model relies on the diagnostic tool to identify the status-quo of enterprises and propose relevant guidelines to achieve marketing benefits with customer intelligence. The diagnostic tool consists of a set of business questions covering eight dimensions, including product-aware intelligence, customer-DNA intelligence, customer experience intelligence, customer value intelligence, CI strategy, CI data, customer analytics, and key performance indicators (Table 5.7). Each dimension has two questions with an associated scoring from 1 to 5 (1 being "Strongly Disagree", 5 being "Strongly Agree"). Adding up all 8 scores and dividing by 8 to get the overall score of the maturity level of customer intelligence. The score for each dimension is visualized through a radar chart as illustrated in Figure 5.14.

Table 5.7
Business questions for the CI diagnostic tool

Questions	**Scores**
Product-aware Intelligence: 1. How well your products/services can satisfy customer needs? 2. How innovative are your products/services?	
Customer-DNA Intelligence 1. How well do you know your customers? 2. How effectively do your customer segments respond to your marketing campaigns?	
Customer Experience Intelligence 1. How well do you manage the customer journey? 2. How satisfied are your customers with their web experience?	
Customer Value Intelligence 1. How profitable are your customers? 2. How does your enterprise engage to create value with customers?	
Customer Intelligence (CI) Strategy 1. How robust is your enterprise to support a CI strategy? 2. How well established are organizational processes to support CI operations?	
CI Data 1. How well does your enterprise collect customer data? 2. How well does your enterprise apply customer data?	
Customer analytics 1. How familiar are you with data mining techniques? 2. How well do you analyze data to support marketing decisions?	
Key performance indicators (KPI) 1. How well do you apply KPIs to support marketing decisions? 2. How effective are current KPIs in supporting marketing decisions?	
Total	**/8**

Source: Adapted from Chaffey and Ellis-Chadwick (2019)

Figure 5.14
The diagnostic tool for customer intelligence



Source: Dam (2021)

Based on the accumulated score of the eight dimensions, there are three maturity levels as follows: Developing (1-4), Intermediate (5-8), and Mature (9-10) (Gudfinnsson et al., 2015). Relevant guidelines are recommended to help your enterprises reach a higher level are presented in detail in Table 5.8.

Table 5.8
The maturity model of customer intelligence for marketing benefits

CI dimension	Developing Level	Intermediate Level	Mature Level
Product-aware intelligence	Satisfying customer needs	Personalizing products/services based on customer preferences	Matching products with context-aware data of customers
Customer DNA intelligence	Segmenting relevant customer preference patterns	Targeting the most profitable segments	Positioning to develop brand equity
Customer experience intelligence	Standardizing customer experience	Personalizing customer experience	Personalizing customer experience for customer co-creation
Customer value intelligence	Standardizing the pricing strategy	Personalizing the pricing strategy	Negotiating the pricing strategy for customer co-creation
CI Strategy	A strategy supporting CI within the marketing department	A strategy supporting CI across all departments	The continuous evolution of the CI strategy
CI Data	Diversifying different types of data	Integrating different sources of data	Acquiring real-time data
Customer Analytics	Descriptive analytics	Predictive analytics	Prescriptive analytics
KPIs	KPIs are used in the marketing and sales department	KPIs are developed into digital dashboards based on the specific needs of each department within an enterprise	An interconnected dashboard with real-time KPIs is developed to keep track of all activities

Source: Dam (2021)

The developing level of CI (score from 1 to 4). Firstly, your enterprise can start by developing a strategy supporting CI within the marketing and sales department. It is suggested to learn more about customers by diversifying demographic, behavioral, psychographic data, and transactional data. At this stage, it is significant to define your business objectives and determine how customer intelligence helps you achieve these objectives. Then you can map out how your customer profiles correspond with products and buying journeys. Another important task to consider is to define your KPIs that need support from customer intelligence. Knowing specific KPIs for marketing decisions help your enterprises identify relevant data sources, types of customer intelligence, and analytic techniques. At this point, your enterprise should focus on product-aware intelligence to develop products/services that meet customer needs. You can rely on customer DNA intelligence to define relevant customer segments. Marketers should consider standardizing the web experience along with the pricing strategy with the support of customer intelligence.

The intermediate level of CI (score from 5 to 8). Your enterprise has started using customer intelligence to support marketing decisions. To improve data-driven decisions, your enterprise should integrate different sources of customer data. The more diverse data sources, the smarter customer intelligence. The diverse data allows you to adopt complicated predictive analytics to improve marketing performance. At this level, executives should consider developing KPIs into digital dashboards based on the specific needs of each department. Product-aware intelligence should leverage its value by personalizing products/services based on customer preferences. Customer DNA intelligence also supports your enterprises to target the most profitable segments. Concerning customer experience intelligence, your website should be able to personalize the experience of users (Huang & Rust, 2021). Finally, customer value intelligence can be used to personalize the pricing strategy so that customers are more likely to make a purchase.

The mature level of CI (score from 9 to 10). Your enterprise can consider acquiring real-time data and applying prescriptive analytics in developing an interactive dashboard with continuously updated KPIs. The non-stop evolution of the customer intelligence strategy should spread out across departments. The value of customer intelligence is leveraged to a higher level. In this light, product-aware intelligence can be applied to match products/services with context-aware data of customers. Context-aware data include data related to emotions, locations, timings, companions, and activities of customers. Moreover, customer DNA intelligence aims at positioning customers with a place that your enterprise wants to occupy in the perception of customers compared to other competitors. In terms of customer experience, your enterprise can attempt to personalize customer experience for customer co-creation (Liang & Liu, 2018; Rakthin et al., 2016). By exchanging values with customers, your enterprises can co-create values with customers through their knowledge, experience, and networks. Accordingly, customer value intelligence allows your enterprise to negotiate the pricing strategy to promote customer co-creation (Balducci & Marinova, 2018). The nature of real-time data at this level enables the price negotiation to timely respond to customers' reactions to the price (Huang & Rust, 2021; López-Robles et al., 2019).

CHAPTER 6
CONCLUSION

This chapter justifies the research theme of the thesis through the discussions on theoretical and practical contributions. Furthermore, the chapter discusses the future direction, research limitations, and research ethics of the thesis. The last section of the chapter concludes with the originality and implications of this study in responding to changes in customer intelligence in the age of big data and leveraging its value toward marketing benefits.

6.1 THEORETICAL AND PRACTICAL CONTRIBUTIONS

This section attempts to highlight the theoretical and practical contributions of the thesis. Theoretical contributions focus on enriching the literature whereas the practical contributions emphasize the support for enterprises.

6.1.1 Theoretical contributions

Considering the research gap in customer intelligence, the thesis makes significant theoretical contributions by updating the definition of customer intelligence in the age of big data through the comprehensive literature review over the past 20 years. The thesis also demystifies different types of customer intelligence with specific marketing benefits and proposed the CIMB model. Lastly, the findings of the thesis will be of interest to the cultural sector by enriching the literature on customer intelligence and connecting service science to this sector.

A comprehensive review of customer intelligence over the past 20 years was conducted to reveal the revolution in this research stream. The literature review also reveals research gaps which are condensed as research questions. Each research gap can be an interesting research direction for future scholars. Considering the research gap, the study proposes a revised definition of customer intelligence with modifications from big data. This novel definition of customer intelligence deals with the constraints of existing definitions by covering the three dimensions of management, organization, and technology of service science. Such modifications would extinguish the proposed definitions from previous studies.

In addition, the concept of customer intelligence is clarified into four types including product-aware intelligence, customer DNA intelligence, customer experience, and customer value. Relevant data types, data sources, analytic techniques, and applications for each type of customer intelligence are also elucidated. The study has also enriched the literature by exploring different aspects of customer intelligence in light of marketing decisions. Therefore, the thesis has made a significant theoretical contribution by bridging the gap between information systems (particularly, customer intelligence and business analytics) and marketing.

Marketing literature related to customer intelligence is relatively sparse (Lau et al., 2016; Li & Li, 2013; Liang & Liu, 2018), prompting the motivation of this thesis to study customer intelligence and develop the CIMB model. In terms of theoretical implications, the reviewed literature discloses interesting findings on customer intelligence. It also identifies relevant constructs associated with customer intelligence in the age of big data such as customer co-creation, customer analytics, marketing benefits, and so on. In addition, the proposed model would help scholars have an overview picture of customer intelligence and facilitate future researchers to extend this research stream. The study makes significant theoretical contributions by revealing interesting findings. This is one of the first conceptual models of customer intelligence, which comprehensively covers the service science. In the matrix of the customer intelligence research stream, the study clearly defines the most relevant constructs related to customer intelligence. The model aims at assisting enterprises to stay on track in acquiring and applying customer intelligence. Subsequently, the CIMB model serves as a roadmap for enterprises to create, manage, and amplify the value of customer intelligence.

As the literature recognizes little connection between marketing and the cultural sector (Botti, 2000; Colbert, 2003; Fillis, 2002), this thesis would make a significant theoretical contribution to the cultural sector. The thesis provides a comprehensive literature review of customer intelligence for cultural SMEs/SMOs with a focus on value creation towards marketing benefits. The number of reviewed articles is selected from a broad range of scientific journals to demonstrate a multifaceted spectrum of scholars and opinions in this research field. The findings of this thesis reveal the big picture of how cultural SMEs/SMOs take advantage of customer intelligence. Literature has a few studies that have synthesized and reviewed the literature in relation to the application of customer intelligence to the cultural sector. Therefore, this thesis can be considered as the pioneered literature review, which fulfills a significant gap in the cultural sector.

Considering the fact that the cultural sector often neglects the significance of value creation for marketing benefits (Chianese et al., 2013; Filip et al., 2015; Jafari et al., 2013; Katz-Gerro, 2004), the value proposition from customer intelligence to cultural services/products would open up new research avenues for future scholars. Based on the literature review and proposed model, scholars can examine other relevant research directions, particularly the research stream reconciling service science and marketing in the cultural sector. In fact, few studies link the two different domains – service science and the cultural sector. Therefore, the thesis can be a great source of reference for researchers to enrich literature in this domain.

6.1.2 Practical contributions

This section gives prominence to the practical contributions in achieving competitive advantages from customer intelligence in the age of big data. Enterprises can rely on this study to guide their strategy in adopting customer intelligence. With regards to the cultural sector, the practical contribution lies in improving the management, organization, and technology dimensions of cultural SMEs/SMOs. Lastly, the thesis contributes in several ways to customer value co-creation and survival from the Covid-19 pandemic.

The proposed model can make critical contributions to enterprises as customer intelligence equips them with competitive advantages to overcome challenges in the age of big data. This study sheds light on the complex nature of customer intelligence in the era of big data. Considering such complexity, the proposed model would assist enterprises to stay on track by identifying the right customer data for the right customer intelligence corresponding with the right marketing decisions. The proposed model can serve as a roadmap for enterprises to avoid losing track of creating value from customer intelligence. Enterprises can confide in the model to determine relevant types of customer intelligence that match their analytic capabilities and strategic objectives.

With regard to practical implications, customer intelligence is applied in different aspects for marketing benefits, including predicting customers' needs, customer segmentation, customer co-creation, customer experience, customer lifetime value estimation, and so on (Cooke & Zubcsek, 2017; Yan et al., 2020). In fact, enterprises are overwhelmed to adopt customer intelligence for marketing benefits. However, they do not know where to start and what benefits to focus on (Huang & Rust, 2018; Jouny-Rivier et al., 2017). For this reason, this study makes a significant implication in guiding enterprises for customer intelligence adoption. The maturity model in Chapter 5 can serve as a diagnostic tool to tell enterprises about their status quo while proving detailed guidelines for the current, emerging, and future practices.

Marketing practice in the cultural sector lacks focus on customer orientation; as a consequence, cultural SMEs/SMOs find it challenging to understand customer preferences and create value for marketing benefits (Lee, 2005; Ruiz et al., 2017). Most SMEs/SMOs apply marketing in arts as an advertising tool and just focus on transaction-based activities (Fillis, 2002; Rentschler, 2002). Otherwise speaking, marketing in arts and cultural content is the application of a set of marketing techniques to increase sales (Lee, 2005; Lee & Lee, 2017). Therefore, the study of customer intelligence in the cultural sector would support cultural SMEs/SMOs to go beyond such applications. Cultural SMEs/SMOs can achieve several marketing benefits from customer intelligence. Not only is customer intelligence implemented for cultural service development, but also it is applied to the restructuring of the dimensions of management, organization, and technology of cultural SMEs/SMOs.

From the dimension of service as economic exchange between customers and service providers, customers can also receive economic value for the contribution of knowledge, skill, and experience. Consequently, the thesis holds important implications for accelerating customer co-creation for enterprises. Enterprises can rely on the results of the thesis to gain a comprehensive understanding of resources, value, and mechanisms with relevance to customer co-creation for marketing benefits. The thesis enables service providers to apply their resources and offer value to customers through appropriate mechanisms. The literature review along with the proposed model can serve as the starting point for enterprises to restructure and adapt to changes in the dimensions of organization, management, and technology in the age of big data.

Considering the challenges of the COVID-19 pandemic, customer intelligence has significantly reinforced its role in helping cultural SMEs/SMOs survive from the crisis. The application of customer intelligence in adapting business practice through the support of technology would be an ideal temporary solution to deal with the restrictions of social distance (D'Amours, 2020; Nuovo, 2020). However, the significant point to ponder is that this study does not over-focus on the dimension of technology, which is a common mistake for most enterprises in the revolution of adopting customer intelligence (Sutcliff et al., 2019; Tabrizi et al., 2019). In addition, with the focus on customer intelligence for marketing benefits, this thesis highlights the importance of customers along with relevant considerations on technology, management, and organization of cultural SMEs/SMOs. Therefore, the thesis would make a great contribution to enterprises, especially cultural SMEs/SMOs to gain competitive advantages in the fierce competition of the era of big data.

6.2 FUTURE RESEARCH DIRECTIONS

For future research directions, the CIMB model will be further validated in other sectors, particularly the export sector in Vietnam. Subsequently, a customer intelligence tool for marketing benefits in the export sector will be developed. Another future research direction involves context-aware customer intelligence systems.

The proposed model of customer intelligence will be further applied to other business sectors in addition to the cultural sector. In the era of big data, the process of internationalization is considered a key factor for economic growth, especially in emerging countries. A deep understanding of local markets and customers plays an indispensable role in the success of the process. Therefore, the proposed model of customer intelligence for marketing benefits will be validated in the export sector. In fact, the first phase of the residence in enterprises was conducted with export firms in Vietnam. Therefore, the validation of the proposed model is expected by these firms to support internationalization in Vietnam.

During the residence in exporting firms, the author has also acknowledged the need for a tool that can apply customer intelligence to support the decisions related to market penetration. Therefore, a customer intelligence tool that aims at helping SMEs in the export sector penetrate international markets will be developed based on the CIMB model. By taking advantage of customer intelligence, the tool enables SMEs to overcome their difficulties by empowering managers to collect, analyze, use, and disseminate relevant customer intelligence for exporting activities. With the support of Institut de recherche sur les PME (INRPME) and Danang University of Economics, several exporting SMEs in Quebec and Vietnam are willing to experience the tool.

Finally, another instantiation which is called a context-aware customer intelligence system will be developed to validate the proposed model. Particularly, this system focuses on the science, management, and engineering dimensions in the transformation to a service-based economy (Maglio & Spohrer, 2013; Spohrer et al., 2007). The *management dimension* aims at applying customer intelligence to specific business cases through a context-aware artificial intelligence (AI) based interface. The *science dimension* aims at applying customer analytics to transform customer data into customer intelligence and context-aware intelligence. Finally, the *engineering dimension* focuses on acquiring, integrating, and classifying data from different sources. This research focus addressed the Future Challenge Areas in giving prominence to the emerging economic, societal, and knowledge needs for Canada to improve the decision-making process across all sectors towards a better future. Indeed, it responds to one of the future global challenges, called "Working in the Digital Economy" by focusing on customer intelligence as a part of artificial intelligence to support service innovation and adjust business models. Thus, the proposed research direction leverages the value of customer intelligence for marketing benefits.

6.3 LIMITATIONS

This section presents limitations of the case study strategy related to subjectivism of researchers, generalizability of research results, and data analysis technique. Justifications for overcoming these limitations are also discussed as follows.

In terms of research methodology, the case study strategy has been suspicious of scientific rigor because the interpretation of the case depends on the subjectivism of researchers (Baxter & Jack, 2008; Tellis, 1997). Considering the purpose of this research is to explore how customer intelligence is applied for supporting marketing benefits of enterprises, particularly for cultural SMEs/SMOs, the case study strategy works reasonably for this nature. Dealing with the subjectivism of researchers, data triangulation from various sources would ensure the convergence of information in the research results (Thornhill et al., 2009). Accordingly, the author also analyzes other data sources from POS systems, Google Analytics, and Facebook Insights provided by cultural organizations that were interviewed. Finally, the subjectivism of the author may happen in the process of translating the verbatim from French to English. To void this issue, the author has a French native speaker verify the translation to ensure the quality.

Another limitation of the case study is the generalizability of the results (Robson & McCartan, 2016). It is argued that the volume of data along with the time restrictions makes it difficult for the results of a case study to represent the research population (Liu & Shi, 2015; Yin, 2003). Concerning this limitation, a multiple case study strategy was conducted to provide a better overview of the cultural sector. Furthermore, the author adopts the mixed strategy, consisting of intra-case and inter-case analysis, to increase the generalizability of the research results.

One of the pitfalls of the thematic analysis is the poor analysis of data that results from irrelevant themes (Boyatzis, 1998; Patton, 1990). Considering this issue, the author carefully follows the phases of thematic analysis to ensure that there are no overlapped or inconsistent themes. Besides, the entire data set will be analyzed across themes to gain a comprehensive understanding of responses from interviewees. Finally, the thesis pays attention to the consistency between the theoretical model and logical arguments.

6.4 RESEARCH ETHICS

With regards to research ethics, the ethics certificate is applied and approved by Université du Québec à Trois-Rivières. This section also touches upon the privacy and anonymity of collected data to set the seal on the research ethics.

To ensure the research ethics of the thesis, the ethics certificate from Université du Québec à Trois-Rivières is obtained. The focal point is to ensure compliance with the principles and procedures for research ethics. Furthermore, the author also prepares a consent form for potential participants to take part in the data collection process. The consent form is presented in Appendix A of the document for further reference. The consent form informs participants of the purpose and nature of the thesis. Accordingly, the research is only for academic purposes. The consent form also confirms that the participation is voluntary, and the interviews may be tape-recorded if necessary. All the collected information is kept strictly and confidentially.

The privacy and anonymity of collected data are ensured so that participants can feel free to participate in the data collection process (Robson & McCartan, 2016). Collected data are coded anonymously and then stored in safe places for privacy (Thornhill et al., 2009). From the side of the researcher, the author is committed to collecting data in an honest, unbiased, and professional way. The analysis of data is not manipulated. The author also considers possible physical and mental risks that might happen to participants during the data collection process.

6.5 CONCLUSION

The age of big data has stimulated the need to take advantage of customer intelligence to survive and thrive in the fierce competition. Enterprises, particularly cultural SMEs/SMOs, are under pressure of making and improving marketing decisions. This triggers the quest for customer intelligence to achieve marketing benefits, which highlights the significance of the research focus of the thesis. Therefore, the study aims at developing a conceptual model of customer intelligence for marketing benefit considering the context of SMEs/SMOs in the cultural sector. To conclude, the section presents the summary of the thesis along with the emphasis on the originality and implications.

Intending to demystify customer intelligence, the study presents a systematic literature review on customer intelligence in the age of big data. This literature review provides a comprehensive overview of research on customer intelligence with an emphasis on marketing benefits. Through the literature, relevant constructs related to customer intelligence are identified and developed into the CIMB model. The in-depth analysis of the reviewed articles discloses noteworthy under-researched areas as research gaps in customer intelligence. These research gaps are also condensed into research questions. Each research question can be a concrete idea for future research directions. Subsequently, a detailed research design is proposed to prepare for the data collection process. The research design discusses relevant epistemology, approach, strategies, and data collection techniques. Based on the research results, discussions on the current, emerging, and future practices of the studied cases are presented. The thesis also discusses the applicability of the proposed model with the demonstrations of the interactive dashboards. The research results also reveal the maturity of models of customer intelligence adoption. The maturity model would help enterprises aware of their current status and readiness for adopting customer intelligence.

Compared to previous works, the original contribution of the thesis lies in the focus on customers by optimizing marketing decisions and leveraging the value creation from customer intelligence for marketing benefits. Instead of overemphasizing the importance of technological changes, the digital transformation should start with customers and for customers. In the era of big data, most enterprises aim at technological upgrades in acquiring customer intelligence. They often ignore the role of restructuring the organizational and strategic viewpoints for customer intelligence (Davenport & Spanyi, 2019). Considering this reflection, this study examines different dimensions of management, science, and engineering under the lens of service science. Through the proposed model, customer intelligence will recur into the dimensions of science, management, and engineering instead of producing one-off products/services (Libert et al., 2015). This originality would extinguish this study from previous studies with a significant contribution.

The results of this thesis indicate interesting findings from the literature review combined with data analysis of enterprises, particularly SMEs/SMOs in the cultural sector. Even though research on customer intelligence is supposed to focus on customers, it seems that not many studies make the connection in the applications of customer intelligence for the cultural sector. Consequently, the thesis plays an important role in guiding and reminding enterprises to shift the focus back on customers instead of pursuing technological investment. Shifting the focal point to customer intelligence for marketing benefits, the thesis has responded to the call of enterprises, particularly cultural SMEs/SMOs, in helping them survive in the age of big data. Especially in the COVID-19 crisis, customer intelligence can provide relevant solutions for cultural SMEs/SMOs to deal with turbulences from the external environment.

APPENDIX A

CONSENT FORM FOR THE INTERVIEW

Consent Form

Thank you for reading the information sheet about the interview. If you are happy to participate then please complete and sign the form below. Please initial the boxes below to confirm that you agree with each statement:

	Please Initial box:
I confirm I have had the purpose and nature of the study explained to me in writing and I have had the opportunity to ask questions about the study	☐
I understand that my participation is voluntary and that I am free to withdraw at any time without giving any reason and without there being any negative consequences. In addition, should I not wish to answer any particular question or questions, I am free to decline.	☐
I understand that my responses will be kept strictly confidential. I understand that my name will not be linked with the research materials and will not be identified or identifiable in the report or reports that result from the research.	☐
I agree for this interview to be tape-recorded. I understand that the audio recording made of this interview will be used only for analysis and that extracts from the interview, from which I would not be personally identified, may be used in any conference presentation, report or journal article developed as a result of the research. I understand that no other use will be made of the recording without my written permission, and that no one outside the research team will be allowed access to the original recording.	☐
I agree that my anonymised data will be kept for future research purposes such as publications related to this study after the completion of the study.	☐
I agree to take part in this interview.	☐

____________________	____________	______________
Name of participant	Date	Signature
____________________	____________	______________
Principal Investigator	Date	Signature

To be counter-signed and dated electronically for telephone interviews or in the presence of the participant for face-to-face interviews

Copies: *Once this has been signed by all parties the participant should receive a copy of the signed and dated participant consent form, and the information sheet. A copy of the signed and dated consent form should be placed in the main project file which must be kept in a secured location.*

APPENDIX B
ETHICS CERTIFICATE

UQTR
Université du Québec à Trois-Rivières
Décanat de la recherche et de la création

Le 2 février 2021

Monsieur Nguyen Anh Khoa Dam
Étudiant
Département de marketing et systèmes d'information

Monsieur,

Le comité d'éthique a reçu votre demande de certification pour le projet **L'intelligence client à l'ère des données massives: un modèle pour les PME/PMO du secteur culturel** en date du 8 janvier 2021.

Lors de sa 273e réunion tenue le 22 janvier 2021, le Comité d'éthique, après analyse, a émis un avis favorable à l'approbation éthique de votre projet mentionné ci-dessus conditionnellement à l'ajout de certaines précisions ou modifications à lui apporter.

Sur le plan du recrutement et des participants, le comité vous demande de :

- Fournir une lettre d'entente de l'organisme Synapse C confirmant leur collaboration au projet de recherche;
- Fournir les informations demandées sur les participants que vous recruterez dans les organismes pour participer à l'entretien (sections 4.1, 4.2 et 4.3 de la demande de certification éthique);
- Prévoir que les coordonnées de l'équipe de recherche seront transmises aux personnes intéressées à participer à la recherche plutôt que les coordonnées de ces personnes soient transmises à l'équipe de recherche.

Sur le plan de la confidentialité, le comité vous demande de spécifier la durée de conservation des données (section 5.1 de la demande de certification éthique).

Dans le message de recrutement qui sera envoyé aux organismes, le comité vous demande d'utiliser un numéro de téléphone professionnel ou privilégier l'utilisation du courriel.

Dans le formulaire d'information et de consentement, le comité vous demande, dans la section « Objectifs et résumé du projet de recherche », d'ajouter un espace entre le 1er et le 2e paragraphe.

UQTR
Université du Québec
à Trois-Rivières
Décanat de la recherche et de la création

En raison de la situation de pandémie de la COVID-19, les recherches avec des êtres humains en présentiel doivent être autorisées par le sous-comité de reprise des activités de recherche. Je vous invite à consulter la page web de l'UQTR sur la COVID-19, pour obtenir des renseignements supplémentaires. Les étudiants doivent se référer à leur directeur de recherche.

Dans le but d'accélérer l'émission de votre certificat, vous pouvez me transmettre les documents par courriel au (cereh@uqtr.ca). Si les compléments d'information et les modifications apportées répondent aux attentes signifiées du Comité, un certificat sera émis.

Je vous rappelle que, conformément à la Politique d'éthique de la recherche avec des êtres humains, vous ne pouvez entreprendre votre recherche sans l'approbation finale du comité d'éthique de la recherche.

Veuillez agréer, Monsieur, mes salutations distinguées.

LA SECRÉTAIRE DU COMITÉ D'ÉTHIQUE DE LA RECHERCHE

FANNY LONGPRÉ
Agente de recherche
Décanat de la recherche et de la création

FL/nr

c. c. MM. Thang Le Dinh et William Menvielle, professeurs au Département de marketing et systèmes d'information

APPENDIX C

DATA NON-DISCLOSURE AGREEMENT

SYNAPSE C

ENTENTE MUTUELLE DE NON-DIVULGATION
ENTENTE DE GESTION DE DONNÉES

Conclue en date du 18 de février 2021 (« **Date d'effet** »)

ENTRE :	**PÔLE SUR LES DONNÉES MASSIVES EN CULTURE (Synapse C)**, personne morale dûment constituée, ayant son siège social au 1435 rue St-Alexandre, bureau 420, Montréal, Québec, H3A 2G4 (ci-après désigné le « **Pôle** »)
ET :	**KHOA NGUYEN ANH DAM**, étudiant inscrit au programme de doctorat à l'Université du Québec à Trois-Rivières (ci-après désigné l' « **Étudiant** »)
ET :	**THÉÂTRE JEAN DUCEPPE**, personne morale dûment constituée, ayant son siège social au 260, boul. de Maisonneuve Ouest, 2e étage, Montréal, Québec, H2X 1Y9 (ci-après désignée l'« **Organisation** »)

Le Pôle, l'Étudiant et l'Organisation sont désignés individuellement une « Partie » et collectivement les « Parties ».

ATTENDU QUE les Parties sont engagées dans des discussions relatives au projet de recherche « *A decision support tool for promoting new business models of cultural organisations in the context of COVID-19 crisis* » (le « **Projet** ») supervisé par le Professeur Thang le Dinh (le « **Professeur** ») de l'Université du Québec à Trois-Rivières, où des données appartenant à l'Organisation seront compilées et analysées, du 19 de février 2021 au 15 de mai 2021 (les « **Discussions** ») ;

ATTENDU QUE le Pôle et l'Organisation sont engagés dans des discussions relatives au projet « Mutualisation des données et analyses » depuis octobre 2020 et que le Pôle entend partager des données appartenant à l'Organisation à l'Étudiant ;

ATTENDU QUE les données appartenant à l'Organisation seront précédemment mutualisées et dépersonnalisées par le Pôle et l'Étudiant avant d'être analysées (les « **Données** ») ;

ATTENDU QUE l'Étudiant et le Pôle, souhaitent exploiter les Données pour répondre aux objectifs communs, tels que définis ci-après ;

ATTENDU QU'afin de permettre ou de faciliter l'accomplissement de leurs obligations dans le cadre des Discussions, les Parties peuvent divulguer l'une à l'autre de l'**Information confidentielle** (telle que définie ci-dessous) ;

ATTENDU QUE les Parties entendent s'échanger certaines Informations confidentielles pour les fins du Projet ;

ATTENDU QUE les Parties désirent préciser les conditions selon lesquelles elles sont prêtes à divulguer de l'Information confidentielle et selon lesquelles elles s'obligent à conserver la confidentialité de cette information dans ce contexte ;

ATTENDU QUE les Parties estiment qu'il est essentiel de préserver la confidentialité de l'Information confidentielle et désirent prévoir par cette entente mutuelle de non-divulgation (l'« **Entente** ») les modalités permettant de parvenir à ces fins ;

ATTENDU QUE chaque **Partie** (telle que définie ci-dessous) déclare et garantit à l'autre qu'elle possède l'autorité, la capacité et le plein pouvoir de conclure la présente Entente et de s'acquitter de ses obligations, que la présente Entente est dûment approuvée et que sa signature a été autorisée et constitue une obligation valide et exécutoire, qui lui est pleinement opposable selon les termes prévus aux présentes ;

PAR CONSÉQUENT, LES PARTIES CONVIENNENT DE CE QUI SUIT :

1. DÉFINITIONS

Aux fins de la présente Entente :

1.1 **« Contrôle »** : désigne, par rapport à une personne donnée, toute autre personne qui, directement ou indirectement, contrôle cette personne ou une ou plusieurs des entités de son groupe ou est contrôlée par elles ou qui est sous le contrôle commun direct ou indirect de cette personne ou d'une ou plusieurs des entités de son groupe. Pour l'application de cette définition, une personne sera réputée en contrôler une autre i) si elle détient, en propriété effective ou au registre, plus de cinquante pour cent (50 %) de ses actions avec droit de vote ou ii) si elle a la capacité d'élire une majorité des membres de son conseil d'administration ;

1.2 **« Information confidentielle »** : désigne toute information verbale ou écrite, y compris toute information échangée électroniquement ou accessible via une salle virtuelle de données, identifiée comme confidentielle ou non, incluant celle fondée en totalité ou en partie sur celle-ci, obtenue directement ou indirectement pendant l'exécution de l'Entente ou avant sa signature par une des Parties ou une entité sous son Contrôle (la « **Partie Réceptrice** ») de l'autre Partie ou une entité sous son Contrôle (la « **Partie Divulgatrice** ») et reliée, notamment : a) aux actifs, produits, services ou technologies développés ou étant la propriété de la Partie Divulgatrice, incluant tout droit de propriété intellectuelle ; b) aux opérations, aux employés, à l'entreprise ou aux finances de la Partie Divulgatrice incluant notamment les Renseignements personnels (tels que définis ci-dessous), les états financiers et projections, la détermination des prix, le marketing ainsi que toute autre information financière ou stratégique ; c) l'existence ou les modalités de la présente Entente ainsi que toute information entourant les discussions des Parties avant la signature de l'Entente. L'absence de mention par la Partie Divulgatrice que l'information est confidentielle n'exempte nullement la Partie Réceptrice de l'obligation de traiter confidentiellement quelque information que l'autre Partie, agissant raisonnablement, considérerait comme confidentielle ;

Sauf pour les Renseignements personnels, l'Information confidentielle n'inclut toutefois pas : (i) l'information qui, au moment de la communication, est disponible publiquement sans que celle-ci ait été rendue publique suite à un défaut de la Partie Réceptrice ; (ii) l'information qui, après communication en vertu de la présente Entente, est rendue publique sans restriction ou le devient sans défaut de la Partie Réceptrice ; (iii) l'information que la Partie Réceptrice peut démontrer avoir eue en sa possession au moment de la communication et qui n'a pas été acquise d'une tierce partie en violation d'une obligation de confidentialité ; (iv) l'information développée indépendamment par la Partie Réceptrice sans avoir accès à l'Information confidentielle de la Partie Divulgatrice, tel que prouvé par des pièces justificatives ; et (v) l'information pour laquelle la Partie Divulgatrice a donné l'accord écrit préalable pour être divulguée ;

1.3 « **Parties** » : désigne l'Étudiant, l'Organisation et le Pôle et « **Partie** » désigne l'un ou l'autre, selon le cas ;

1.4 « **Renseignements personnels** » : désigne les renseignements, quels que soient leur forme et leur support, concernant un individu identifiable, y compris les informations personnelles du Pôle, de l'Organisation, de leurs clients, employés ou fournisseurs ;

1.5 « **Droits de propriété intellectuelle** » signifie tous les droits de propriété intellectuelle, enregistrés ou non, y compris les droits relatifs aux brevets, droits d'auteur, dessins industriels, topographies de circuits intégrés, obtentions végétales, inventions (brevetables ou non), découvertes, secrets de commerce, savoir-faire, noms de domaine, marques de commerce, noms commerciaux et autres droits reconnus par la loi statutaire ou le droit commun dans ce qui précède, incluant toute demande de protection.

2. RECONNAISSANCE

2.1 La Partie Réceptrice reconnaît que l'Information confidentielle, et tous les droits, titres et intérêts dans celle-ci, demeurent la propriété unique et exclusive de la Partie Divulgatrice ou d'une entité sous son Contrôle, le cas échéant. Par conséquent, la présente Entente ne pourra être interprétée comme octroyant ou conférant à la Partie Réceptrice quelque droit, titre ou intérêt que ce soit dans l'Information confidentielle ;

2.2 La Partie Réceptrice reconnaît et convient que la Partie Divulgatrice ne fait aucune représentation ou garantie en ce qui concerne l'Information confidentielle ou son caractère adéquat ou exact. Sous réserve de ce qui est expressément convenu par écrit, la Partie Divulgatrice ne sera pas responsable pour toute dépense, perte, coût ou dommage résultant de toute utilisation de l'Information confidentielle ou de toute erreur ou omission, quelle qu'en soit la cause ;

2.3 Ni l'une ni l'autre des Parties n'aura d'obligation légale de quelque nature que ce soit en ce qui concerne les Discussions, sauf en ce qui a trait aux questions expressément convenues aux présentes.

3. OBLIGATIONS ET RESPONSABILITÉ

3.1 La Partie Réceptrice devra protéger l'Information confidentielle et en empêcher la divulgation à des tierces parties en adoptant le même degré de diligence et de prudence qu'elle adopterait pour protéger sa propre information confidentielle, mais jamais moins que le standard d'une personne raisonnable. La collecte, l'utilisation, la rétention et la divulgation de Renseignements personnels aux fins de ce contrat sont assujetties aux lois applicables de la protection des renseignements personnels ;

3.2 La Partie Réceptrice divulguera l'Information confidentielle uniquement à ceux de ses dirigeants, employés et conseillers juridiques ou financiers (« **Représentants** ») qui ont besoin de connaître l'Information confidentielle dans le cadre des Discussions, et à condition que lesdits Représentants aient souscrit à des obligations de confidentialité et de non-divulgation essentiellement similaires à celles de la présente Entente, ou plus contraignantes que celles-ci. De plus, la Partie Réceptrice convient (i) d'informer les Représentants, avant de leur donner accès à l'Information confidentielle, des obligations de la Partie Réceptrice aux termes de la présente Entente et (ii) de donner instructions à ces Représentants de traiter l'Information confidentielle conformément à la présente Entente. Nonobstant ce qui précède, la Partie

Réceptrice demeure pleinement responsable de toute violation par les Représentants des obligations prévues aux termes de la présente Entente ou découlant de celle-ci ;

3.3 Nonobstant toute autre disposition des présentes, la Partie Réceptrice ne pourra être tenue responsable de la divulgation de l'Information confidentielle si elle est requise de le faire par les lois canadiennes ou suite à une ordonnance finale d'une cour ou d'un tribunal canadien, à condition cependant, que si la Partie Réceptrice reçoit un subpoena ou quelque autre document semblable exigeant qu'elle divulgue l'Information confidentielle, la Partie Réceptrice en avise la Partie Divulgatrice dans les plus brefs délais afin de permettre à cette dernière de prendre les mesures qui s'imposent pour prévenir et/ou contester la divulgation de cette Information confidentielle ou, selon le cas, s'assurer que la divulgation ne sera faite que sous des conditions strictes de confidentialité.

4. UTILISATION DE L'INFORMATION CONFIDENTIELLE

4.1 Les Données seront entièrement dépersonnalisées avant d'être analysées ;

4.1.1 Le Pôle confirme par la présente que les Données qui seront transférées à l'Étudiant sont entièrement dépersonnalisées, c'est-à-dire qu'elles ne contiennent plus aucun Renseignement personnel, de sorte qu'il n'est pas possible de ré-identifier quelque individu que ce soit, par rétro-ingénierie ou autrement ;

4.1.2 L'Étudiant et le Pôle confirment par la présente que les Données qui seront transférées par l'Organisation à l'Étudiant et au Pôle seront entièrement dépersonnalisées, c'est-à-dire qu'elles ne contiendront plus aucun Renseignement personnel, de sorte qu'il n'est pas possible de ré-identifier quelque individu que ce soit, par rétro-ingénierie ou autrement.

4.2 Les Données seront ensuite exploitées dans le cadre de diverses analyses pour répondre aux objectifs communs suivants des Parties :

- Développement d'un outil d'aide à la décision type tableau de bord pour prendre de meilleures décisions pendant et après la COVID-19 ainsi que pour la transformation numérique ;

- Création d'indicateurs clés de performance (KPI) relatifs aux clients et aux produits pour gérer la transformation numérique du secteur culturel ;

- Développer des tableaux de bord pertinents pour visualiser les données relatives aux clients et aux produits afin de soutenir le processus décisionnel des organismes culturels pendant et après la crise ;

- Expérimenter l'outil d'aide à la décision.

4.3 Sauf autorisation écrite de la Partie Divulgatrice à l'effet contraire, la Partie Réceptrice :

4.3.1 Ne doit pas utiliser l'Information confidentielle de la Partie Divulgatrice pour tout autre objet que celui énoncé et seulement dans la mesure où l'utilisation est expressément permise aux termes de la présente Entente ou raisonnablement nécessaire pour l'exercice de ses droits ou l'exécution de ses obligations dans le cadre des Discussions ;

4.3.2 Doit prendre toutes les mesures nécessaires et appropriées pour préserver la stricte confidentialité de l'Information confidentielle de la Partie Divulgatrice, notamment, sans s'y limiter, contre les risques de perte ou de vol, l'accès non autorisé, la divulgation, la copie, l'utilisation, la modification ou la destruction. Les efforts déployés par la Partie Réceptrice devront l'être avec le même degré de diligence et de prudence que ceux qu'elle déploie pour maintenir et protéger sa propre information confidentielle, mais jamais moins que le standard d'une personne raisonnable ;

4.3.3 Ne doit pas copier ni autrement reproduire l'Information confidentielle, sans avoir obtenu au préalable le consentement écrit de la Partie Divulgatrice, sauf uniquement dans la mesure requise par les Discussions ;

4.3.4 Ne doit pas publier, distribuer ni autrement communiquer ou divulguer, toute Information confidentielle de la Partie Divulgatrice à toute tierce partie, ni divulguer à quiconque le fait que l'Information confidentielle ait été mise à sa disposition en vertu des présentes, sans obtenir le consentement préalable écrit de la Partie Divulgatrice.

5. RETOUR/DESTRUCTION DE L'INFORMATION CONFIDENTIELLE

5.1 Lors de l'expiration ou de la résiliation de la présente Entente ou en tout temps à la demande de la Partie Divulgatrice, la Partie Réceptrice doit retourner à la Partie Divulgatrice toute l'Information confidentielle fournie par cette dernière dans le cadre des Discussions, notamment : les documents, dossiers, équipements ou données informatiques (ou tout autre élément relatif aux présentes, à la clientèle ou aux données des clients) et ce, selon le format et médium alors demandés par la Partie Divulgatrice. Si la Partie Réceptrice ne peut retourner l'Information confidentielle, y compris celle périmée ou celle placée sur un support défectueux, quel que soit le support, la Partie Réceptrice s'engage à détruire ou à effacer de façon permanente et sécuritaire l'Information confidentielle et un dirigeant de la Partie Réceptrice devra certifier par écrit que cette Information confidentielle a été détruite ou effacée sans possibilité de la récupérer et sans en conserver une copie.

6. RECOURS

6.1 Les Parties reconnaissent et conviennent que tout manquement de la Partie Réceptrice à toute disposition de cette Entente peut causer un préjudice irréparable et des dommages irréversibles à la Partie Divulgatrice, lesquels ne peuvent être aisément quantifiables. En de telles circonstances, la Partie Réceptrice pourra, en plus de tous les recours prévus aux présentes ou par la loi, se prévaloir, dans le cadre de toute action devant un tribunal compétent, de tout redressement équitable, y compris une injonction ou toute autre ordonnance de sauvegarde similaire, pour éviter et/ou faire cesser la violation des présentes et en faire respecter les conditions.

7. DATE D'EFFET ET DURÉE

7.1 La présente Entente entre en vigueur à la Date d'effet stipulée ci-dessus et continuera d'être en effet pour une période trois (3) ans à partir de la date de réception par chaque Partie de l'Information confidentielle ;

7.2 Nonobstant les conditions prévues à l'article 7.1 ci-dessus, les obligations prévues aux présentes en ce qui concerne l'Information confidentielle, de même que les recours de la Partie Divulgatrice en cas de violation de ces obligations, demeureront en vigueur indéfiniment pour les Renseignements personnels et les secrets de fabrique.

8. DISPOSITIONS GÉNÉRALES

8.1 Avis. Tout avis requis en vertu de la présente Entente sera présumé reçu au moment où il est remis en mains propres à son destinataire ou trois (3) jours après son envoi, s'il est transmis par courrier recommandé ou certifié, aux adresses des Parties indiquées ci-dessus, ou à toute autre adresse que pourrait fournir une Partie à l'autre par écrit.

8.2 Préséance de l'Entente. Sauf disposition contraire dans les présentes, la présente Entente annule et remplace toutes ententes, conventions, négociations et communications antérieures entre les Parties, qu'elles soient écrites ou orales, et constitue l'entente intégrale entre les Parties pour tout ce qui y est prévu.

8.3 Modification. Aucun changement ou modification à la présente Entente ne sera valide à moins qu'il ne soit fait par écrit, qu'il ne soit clairement identifié comme un changement ou une modification et qu'il ne soit signé par les Parties.

8.4 Cession. Ni l'une ni l'autre des Parties ne peut céder la présente Entente ni aucun de ses droits, intérêts, engagements ou obligations en découlant sans le consentement préalable écrit de l'autre Partie. Sous réserve de ce qui précède, la présente Entente s'appliquera au profit des Parties et de leurs successeurs et ayants droit respectifs de même qu'elle les engagera.

8.5 Indépendance des dispositions. Le fait qu'une disposition de la présente Entente soit, en tout ou en partie, déclarée invalide, illégale ou non exécutoire par un tribunal compétent n'influe en rien sur la validité, la légalité ou le caractère exécutoire des autres dispositions ou parties de dispositions des présentes, qui conserveront leur plein effet.

8.6 Renonciation. Le défaut d'une Partie exiger le respect d'une disposition de la présente Entente à tout moment ne constitue pas une renonciation à l'application des modalités de la présente Entente et ne modifie pas le droit de cette Partie d'exiger subséquemment le respect de cette disposition ou de toute autre disposition de la présente Entente.

8.7 Lois applicables. La présente Entente sera régie par les lois en vigueur dans la province du Québec et sera interprétée conformément à celles-ci, et les Parties acceptent par les présentes de se soumettre à la compétence des tribunaux de la province du Québec pour tout litige résultant de la présente Entente ou encore de la violation ou de l'exécution de celle-ci.

8.8 Signature. La présente Entente pourra être signée en plusieurs exemplaires. Une Partie pourra transmettre à l'autre son exemplaire signé de l'Entente par télécopieur ou par courriel plutôt que de lui en délivrer l'original. Chaque exemplaire signé (y compris chaque copie reçue par télécopieur ou par courriel en version PDF) sera considéré comme un original ; les exemplaires dûment signés formeront ensemble l'Entente.

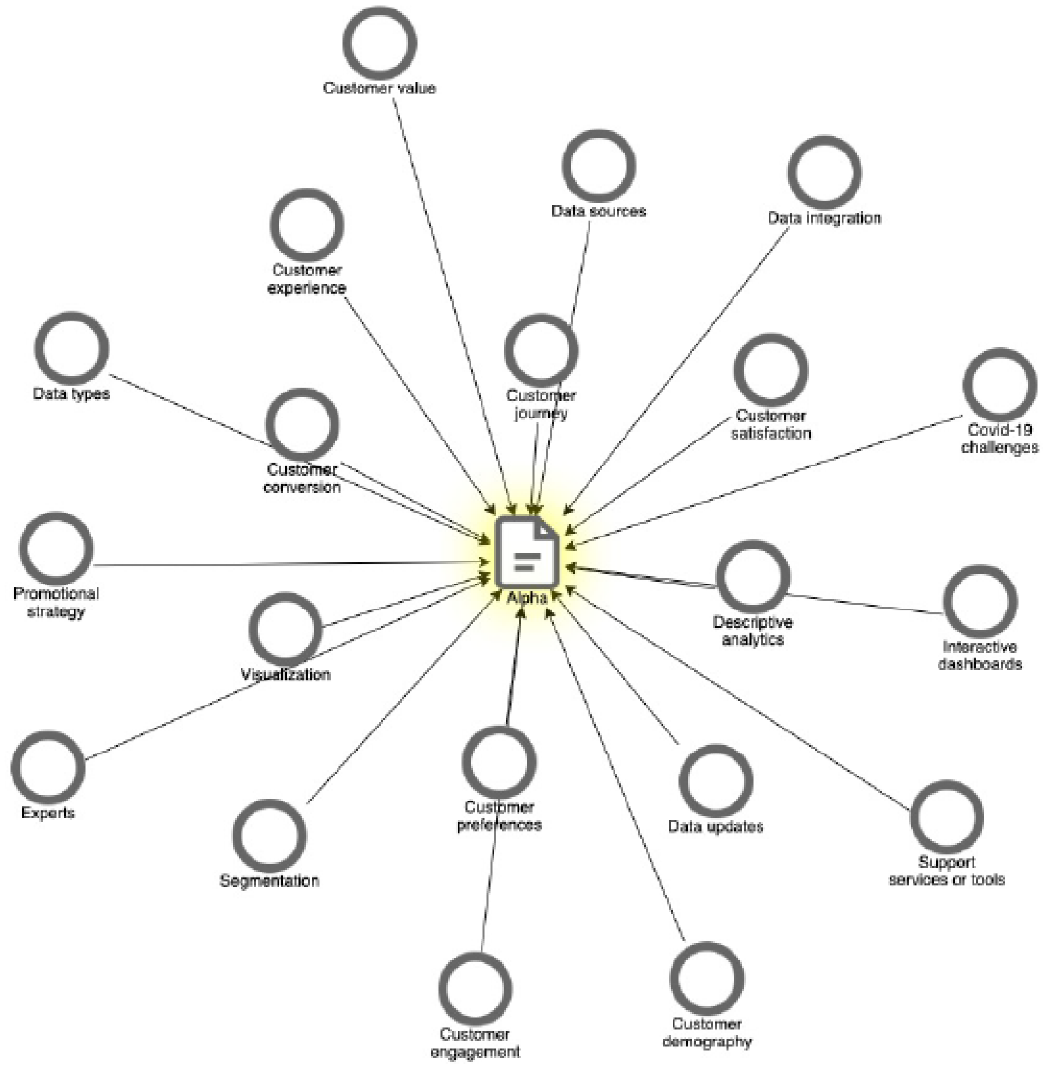
EN FOI DE QUOI, la présente Entente a été signée par les Parties à la date mentionnée ci-avant à la première page.

PÔLE SUR LES DONNÉES MASSIVES EN CULTURE (Synapse C)	**THÉÂTRE JEAN DUCEPPE**
Signature : Diane De Courcy	Signature : ____________
Nom : Diane De Courcy	Nom : ____________
Titre : Directrice générale	Titre : ____________

KHOA NGUYEN ANH DAM

Signature : Danh

APPENDIX D
CODES OF ALPHA



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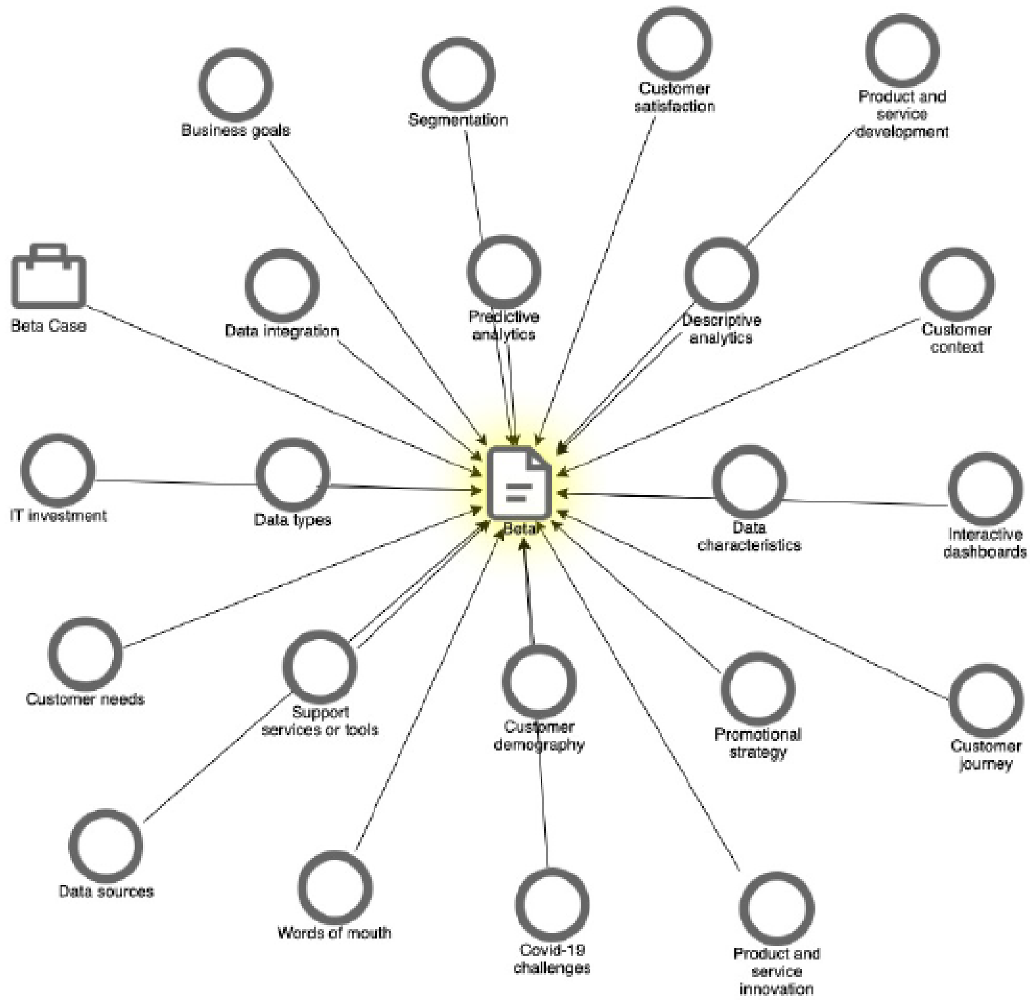
APPENDIX E

CODES OF BETA



Source: NVivo

APPENDIX F

TOP WORDS WEIGHTED PERCENTAGE OF ALPHA

Word	Length	Count	Weighted Percentage
data	4	52	0.93%
customer	8	35	0.63%
information	11	24	0.43%
business	8	23	0.41%
show	4	23	0.41%
question	8	21	0.38%
customers	9	19	0.34%
media	5	18	0.32%
new	3	18	0.32%
social	6	18	0.32%
analysis	8	17	0.31%
model	5	16	0.29%
facebook	8	15	0.27%
newsletter	10	15	0.27%
pandemic	8	15	0.27%
dashboard	9	14	0.25%
analyze	7	13	0.23%
donation	8	13	0.23%
google	6	12	0.22%
right	5	12	0.22%
tickets	7	12	0.22%
value	5	12	0.22%
donors	6	10	0.18%
number	6	10	0.18%
period	6	10	0.18%
rate	4	10	0.18%
transaction	11	10	0.18%
service	7	9	0.16%
theater	7	9	0.16%
ticket	6	9	0.16%

Word	Length	Count	Weighted Percentage
analytics	9	8	0.14%
concrete	8	8	0.14%
conversion	10	8	0.14%
crisis	6	8	0.14%
database	8	8	0.14%
donations	9	8	0.14%
email	5	8	0.14%
engagement	10	8	0.14%
mentioned	9	8	0.14%
networks	8	8	0.14%
often	5	8	0.14%
percentage	10	8	0.14%
production	10	8	0.14%
situation	9	8	0.14%
advertisements	14	7	0.13%
channels	8	7	0.13%
clients	7	7	0.13%
costs	5	7	0.13%
decision	8	7	0.13%
income	6	7	0.13%

Source: NVivo

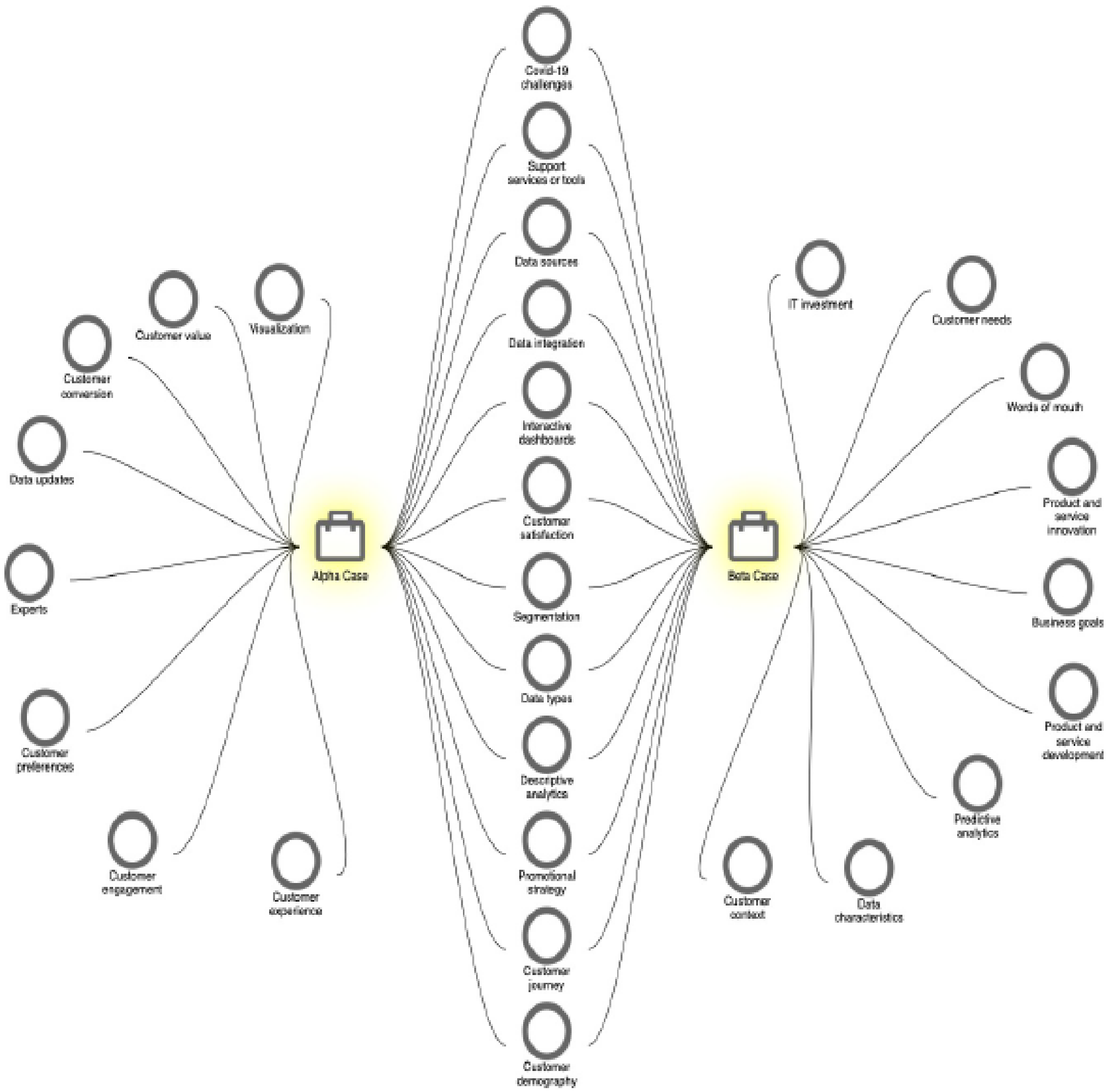
APPENDIX G
TOP WORDS WEIGHTED PERCENTAGE OF BETA

Word	Length	Count	Weighted Percentage
data	4	118	1.16%
customer	8	90	0.88%
museum	6	61	0.60%
information	11	48	0.47%
customers	9	47	0.46%
offer	5	46	0.45%
business	8	44	0.43%
new	3	37	0.36%
products	8	37	0.36%
analytics	9	36	0.35%
covid	5	33	0.32%
media	5	33	0.32%
google	6	31	0.30%
development	11	30	0.29%
pandemic	8	30	0.29%
quebec	6	30	0.29%
question	8	30	0.29%
model	5	29	0.29%
social	6	29	0.29%
facebook	8	27	0.27%
dashboard	9	26	0.26%
intelligence	12	26	0.26%
members	7	26	0.26%
services	8	26	0.26%
income	6	24	0.24%
show	4	24	0.24%
value	5	23	0.23%
analysis	8	22	0.22%
decision	8	22	0.22%
product	7	22	0.22%

Word	Length	Count	Weighted Percentage
school	6	22	0.22%
visitors	8	21	0.21%
right	5	20	0.20%
strategic	9	20	0.20%
newsletter	10	19	0.19%
place	5	19	0.19%
program	7	19	0.19%
activities	10	18	0.18%
improve	7	18	0.18%
partners	8	18	0.18%
arts	4	17	0.17%
management	10	17	0.17%
marketing	9	17	0.17%
project	7	17	0.17%
funding	7	16	0.16%
response	9	16	0.16%
sources	7	16	0.16%
support	7	16	0.16%
virtual	7	16	0.16%
actions	7	15	0.15%
analyze	7	15	0.15%
environment	11	15	0.15%
financial	9	15	0.15%
service	7	15	0.15%

Source: NVivo

APPENDIX H
CASE COMPARISON



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REFERENCE

Akter, S., & Wamba, S. F. (2019). Big data and disaster management: a systematic review and agenda for future research. *Annals of Operations Research, 283*(1-2), 939-959.

Aktinson, P., & Hammersley, M. (1998). Ethnography and participant observation. *Strategies of Qualitative Inquiry. Thousand Oaks: Sage*, 248-261.

Alavi, M., & Leidner, D. E. (2001). Knowledge management and knowledge management systems: Conceptual foundations and research issues. *MIS Quarterly*, 107-136.

Alves, H., Fernandes, C., & Raposo, M. (2016). Value co-creation: Concept and contexts of application and study. *Journal of Business Research, 69*(5), 1626-1633.

Amado, A., Cortez, P., Rita, P., & Moro, S. (2018). Research trends on Big Data in Marketing: A text mining and topic modeling based literature analysis. *European Research on Management and Business Economics, 24*(1), 1-7. https://doi.org/10.1016/j.iedeen.2017.06.002

Anshari, M., Almunawar, M. N., Lim, S. A., & Al-Mudimigh, A. (2019). Customer relationship management and big data enabled: Personalization & customization of services. *Applied Computing and Informatics*(94), 101.

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

Association, A. M. (2015). Customer definition. In *AMA Dictionary*. https://www.ama.org/resources/Pages/Dictionary.aspx?dLetter=C

Baars, H., & Kemper, H.-G. (2008). Management Support with Structured and Unstructured Data—An Integrated Business Intelligence Framework. *Information Systems Management, 25*(2), 132-148. https://doi.org/10.1080/10580530801941058

Baesens, B., Bapna, R., Marsden, J. R., Vanthienen, J., & Zhao, J. L. (2016). Transformational Issues Of Big Data And Analytics In Networked Business. *MIS Quarterly, 40*(4)

Baines, T., Bigdeli, A. Z., Bustinza, O. F., Shi, V. G., Baldwin, J., & Ridgway, K. (2017). Servitization: revisiting the state-of-the-art and research priorities. *International Journal of Operations & Production Management*.

Balducci, B., & Marinova, D. (2018). Unstructured data in marketing. *Journal of the Academy of Marketing Science, 46*(4), 557-590.

Bank, W. (2018). World Bank open data. *World Bank Web site (INTERNET)*.

Barile, S., & Polese, F. (2010). Smart service systems and viable service systems: Applying systems theory to service science. *Service Science, 2*(1-2), 21-40.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of management, 17*(1), 99-120.

Bartolini, I., Moscato, V., Pensa, R. G., Penta, A., Picariello, A., Sansone, C., & Sapino, M. L. (2016). Recommending multimedia visiting paths in cultural heritage applications. *Multimedia tools applications, 75*(7), 3813-3842.

Bassey, M. (1998). Action research for improving educational practice. *Teacher research and school improvement: Opening doors from the inside*, 93-108.

Baxter, P., & Jack, S. (2008). Qualitative case study methodology: Study design and implementation for novice researchers. *The qualitative report, 13*(4), 544-559.

Bazeley, P., & Jackson, K. (2013). *Qualitative data analysis with NVivo*. SAGE publications limited.

Bellenger, G. (2004). *Creating knowledge objects* (Vol. 25).

Bender, C., Boisclair, I., Bramhill, L., Camier, M., Devirieux, S., & Gaquère, G. (2020). *Lettre ouverte signée par les membres du conseil d'administration du CQT*. https://cqt.ca/covid19/info/1320

Beverungen, D., Müller, O., Matzner, M., Mendling, J., & Vom Brocke, J. (2019). Conceptualizing smart service systems. *Electronic Markets, 29*(1), 7-18.

Bianchini, M., & Michalkova, V. (2019). Data analytics in SMEs: trends and policies.

Blee, K. M., & Taylor, V. (2002). Semi-structured interviewing in social movement research. *Methods of social movement research, 16*, 92-117.

Boisnard, M., Tchéhouali, D., & Rioux, M. (2019). Cultural Policies 2.0: Rebuilding the Intervention of Public Authorities. *Digitalization of Society and Socio-political Issues 1: Digital, Communication and Culture*, 139-147.

Boivin, M., & Tanguay, G. A. (2019). Analysis of the determinants of urban tourism attractiveness: The case of Québec City and Bordeaux. *Journal of destination marketing & management, 11*, 67-79.

Boorsma, M. (2006). A strategic logic for arts marketing: Integrating customer value and artistic objectives. *International journal of cultural policy, 12*(1), 73-92.

Bose, R. (2008). Competitive intelligence process and tools for intelligence analysis. *Industrial Management & Data Systems, 108*(4), 510-528. https://doi.org/10.1108/02635570810868362

Botti, S. (2000). What role for marketing in the arts? An analysis of arts consumption and artistic value. *International Journal of Arts Management*, 14-27.

Boyatzis, R. E. (1998). *Transforming qualitative information: Thematic analysis and code development*. sage.

Božič, K., & Dimovski, V. (2019). Business intelligence and analytics for value creation: The role of absorptive capacity. *International Journal of Information Management, 46*, 93-103.

Braganza, A., Brooks, L., Nepelski, D., Ali, M., & Moro, R. J. J. o. B. R. (2017). Resource management in big data initiatives: Processes and dynamic capabilities. *70*, 328-337.

Branda, A. F., Lala, V., & Gopalakrishna, P. (2018). The marketing analytics orientation (MAO) of firms: identifying factors that create highly analytical marketing practices. *Journal of Marketing Analytics, 6*(3), 84-94.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative research in psychology, 3*(2), 77-101.

Breidbach, C. F., & Maglio, P. P. (2016). Technology-enabled value co-creation: An empirical analysis of actors, resources, and practices. *Industrial Marketing Management, 56*, 73-85.

Bryman, A. (2007). The research question in social research: what is its role? *International Journal of Social Research Methodology, 10*(1), 5-20.

Burrell, G., & Morgan, G. (1979). Part I: In search of a framework. *Sociological paradigms and organizational analysis: Elements of sociology of corporate life. London: Heinemann*.

Burrell, L. (2018). Co-Creating the Employee Experience. *Harvard business review*.

Butler, P. (2000). By popular demand: marketing the arts. *Journal of marketing management, 16*(4), 343-364.

Cacciolatti, L. A., & Fearne, A. (2013). Marketing intelligence in SMEs: implications for the industry and policy makers. *Marketing Intelligence & Planning, 31*(1), 4-26. https://doi.org/10.1108/02634501311292894

Camarero, C., Garrido, M. J., & Vicente, E. (2011). How cultural organizations' size and funding influence innovation and performance: the case of museums. *Journal of cultural economics, 35*(4), 247.

Cambra-Fierro, J., Melero-Polo, I., & Sese, F. J. (2018). Customer value co-creation over the relationship life cycle. *Journal of Service Theory and Practice, 28*(3), 336-355.

Castagna, F., Centobelli, P., Cerchione, R., Esposito, E., Oropallo, E., & Passaro, R. (2020). Customer Knowledge Management in SMEs Facing Digital Transformation. *Sustainability, 12*(9), 3899.

Chaffey, D., & Ellis-Chadwick, F. (2019). *Digital marketing*. Pearson UK.

Chari, M. D., Luce, K., & Thukral, I. (2017). Mastering the market intelligence challenge. *MIT Sloan Management Review, 58*(2), 41.

Chaudhuri, S., Dayal, U., & Narasayya, V. (2011). An overview of business intelligence technology. *Communications of the ACM, 54*(8), 88-98.

Chen, H., Chan-Olmsted, S., Kim, J., & Sanabria, I. M. (2021). Consumers' perception on artificial intelligence applications in marketing communication. *Qualitative market research: An international journal*.

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly, 36*, 1165-1188.

Chen, I. J., & Popovich, K. (2003). Understanding customer relationship management (CRM) People, process and technology. *Business Process Management Journal, 9*(5), 672-688.

Chen, T., Drennan, J., Andrews, L., & Hollebeek, L. D. (2018). User experience sharing: Understanding customer initiation of value co-creation in online communities. *European Journal of Marketing, 52*(5/6), 1154-1184.

Chevallier, C., Laarraf, Z., Lacam, J. S., Miloudi, A., & Salvetat, D. (2016). Competitive intelligence, knowledge management and coopetition: The case of european high-technology firms. *Business Process Management Journal, 22*(6), 1192-1211.

Chianese, A., Marulli, F., Piccialli, F., & Valente, I. (2013). A novel challenge into multimedia cultural heritage: an integrated approach to support cultural information enrichment. *2013 International Conference on Signal-Image Technology & Internet-Based Systems*, 217-224.

Chianese, A., & Piccialli, F. (2016). A smart system to manage the context evolution in the Cultural Heritage domain. *Computers Electrical Engineering, 55*, 27-38.

Chung, M., Ko, E., Joung, H., & Kim, S. J. (2018). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*.

Ciurea, C., & Filip, F. G. (2016). New Researches on the Role of Virtual Exhibitions in Digitization, Preservation and Valorization of Cultural Heritage. *Informatica Economica, 20*(4), 26.

Ciurea, C., & Filip, F. G. (2018). Identifying Business Models for Re-use of Cultural Objects by Using Modern ICT Tools. *Informatica Economica, 22*(1), 68-75.

Colbert, F. (2003). Entrepreneurship and leadership in marketing the arts. *International Journal of Arts Management, 1009*(5), 6.

Colbert, F. (2014). The arts sector: A marketing definition. *Psychology & Marketing, 31*(8), 563-565.

Colbert, F. (2017). A brief history of arts marketing thought in North America. *The Journal of Arts Management, Law, and Society, 47*(3), 167-177.

Colbert, F., & Dantas, D. C. (2019). Customer Relationships in Arts Marketing: A Review of Key Dimensions in Delivery by Artistic and Cultural Organizations. *International Journal of Arts Management, 21*(2).

Colbert, F., & St-James, Y. (2014). Research in arts marketing: evolution and future directions. *Psychology & Marketing, 31*(8), 566-575.

Coleman, S., Göb, R., Manco, G., Pievatolo, A., Tort-Martorell, X., & Reis, M. S. (2016). How can SMEs benefit from big data? Challenges and a path forward. *Quality and Reliability Engineering International, 32*(6), 2151-2164.

Cooke, A. D., & Zubcsek, P. P. (2017). The connected consumer: Connected devices and the evolution of customer intelligence. *Journal of the Association for Consumer Research, 2*(2), 164-178.

Cooke, P., & De Propris, L. (2011). A policy agenda for EU smart growth: the role of creative and cultural industries. *Policy Studies, 32*(4), 365-375.

Crandell, C. (2016). Customer Co-Creation Is The Secret Sauce To Success. *Forbes*.

D'Amours, C. (2020). *COVID-19 : des « répercussions foudroyantes » pour les artistes, selon le directeur du Conseil des arts du Canada*. https://ici.radio-canada.ca/nouvelle/1671710/pertes-artistes-millions-aide-gouvernements-coronavirus

Dai, T., Hein, C., & Zhang, T. (2019). Understanding how Amsterdam City tourism marketing addresses cruise tourists' motivations regarding culture. *Tourism Management Perspectives, 29*, 157-165.

Dam, N. A. K., & Le Dinh, T. (2020). A Literature Review of Recommender Systems for the Cultural Sector. *Proceedings of the 22nd International Conference on Enterprise Information, 1*. https://doi.org/10.5220/0009337807150726

Dam, N. A. K., Le Dinh, T., & Menvielle, W. (2019). Marketing Intelligence From Data Mining Perspective – A Literature Review. *International Journal of Innovation, Management and Technology, 10*(5), 184-190.

Dam, N. A. K., Le Dinh, T., & Menvielle, W. (2020). Customer Co-creation through the Lens of Service-dominant Logic: A Literature Review. *AMCIS 2020 Proceedings. 29*.

Dam, N. A. K., Le Dinh, T., & Menvielle, W. (2021a). Key Aspects of Customer Intelligence in the Era of Massive Data. *Asian Conference on Intelligent Information and Database Systems*, 259-271. https://doi.org/10.1007/978-3-030-73280-6_21 (Intelligent Information and Database Systems)

Dam, N. A. K., Le Dinh, T., & Menvielle, W. (2021b). Towards a Conceptual Framework for Customer Intelligence in the Era of Big Data. *International Journal of Intelligent Information Technologies (IJIIT), 17*(4), 1-17.

Dam, N. A. K., Le Dinh, T., & Menvielle, W. (2022). The Quest for Customer Intelligence to Support Marketing Decisions: A Knowledge-Based Framework. *Vietnam Journal of Computer Science, 0*(0), 1-20. https://doi.org/10.1142/s2196888822500208

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48*(1), 24-42.

Davenport, T. H. (2006). Competing on analytics. *Harvard business review, 84*(1), 98.

Davenport, T. H., & Dyché, J. (2013). Big data in big companies. *International Institute for Analytics, 3*.

Davenport, T. H., & Spanyi, A. (2019). Digital Transformation Should Start With Customers. *MIT Sloan Management Review*.

Davis, C. K. (2014). Beyond data and analysis. *Communications of the ACM, 57*(6), 39-41.

Del Vecchio, P., Secundo, G., & Passiante, G. (2018). Analyzing Big Data through the lens of customer knowledge management. *Kybernetes*.

Della Porta, D. (2008). 11 Comparative analysis: case-oriented versus variable-oriented research. *Approaches and methodologies in the social sciences*, 198.

Dictionary, O. (2014). Intelligence. In *Oxford Dictionary*. https://www.lexico.com/en/definition/intelligence

Dinh, T. L., & Dam, N. A. K. (2021). Towards Smart Customer Knowledge Management Systems. *International Conference on Computational Collective Intelligence*, 225-238.

Efrat, K., Gilboa, S., & Yonatany, M. J. I. B. R. (2017). When marketing and innovation interact: The case of born-global firms. *26*(2), 380-390.

Ekstrand, M. D., Riedl, J. T., & Konstan, J. A. (2011). Collaborative filtering recommender systems. *Foundations Trends in Human–Computer Interaction, 4*(2), 81-173.

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of Business Research, 69*(2), 897-904.

Fan, S., Lau, R. Y. K., & Zhao, J. L. (2015). Demystifying Big Data Analytics for Business Intelligence Through the Lens of Marketing Mix. *Big Data Research, 2*(1), 28-32. https://doi.org/10.1016/j.bdr.2015.02.006

Fernandes, T., & Remelhe, P. (2016). How to engage customers in co-creation: customers' motivations for collaborative innovation. *Journal of Strategic Marketing, 24*(3-4), 311-326.

Filip, F. G., Ciurea, C., Dragomirescu, H., & Ivan, I. (2015). Cultural heritage and modern information and communication technologies. *Technological Economic Development of Economy, 21*(3), 441-459.

Fillis, I. (2002). Creative marketing and the art organisation: what can the artist offer? *International Journal of Nonprofit Voluntary Sector Marketing, 7*(2), 131-145.

Fillis, I. (2011). The evolution and development of arts marketing research. *Arts Marketing: An International Journal, 1*(1), 11-25.

Flyvbjerg, B. (2006). Five misunderstandings about case-study research. *Qualitative inquiry, 12*(2), 219-245.

Fotaki, G., Spruit, M., Brinkkemper, S., & Meijer, D. (2014). Exploring big data opportunities for online customer segmentation. *International Journal of Business Intelligence Research (IJBIR), 5*(3), 58-75.

France, C., Merrilees, B., & Miller, D. (2015). Customer brand co-creation: a conceptual model. *Marketing Intelligence & Planning, 33*(6), 848-864.

France, S. L., & Ghose, S. (2018). Marketing analytics: Methods, practice, implementation, and links to other fields. *Expert Systems with Applications, 119*, 456-475. https://doi.org/10.1016/j.eswa.2018.11.002

France, S. L., & Ghose, S. (2019). Marketing analytics: Methods, practice, implementation, and links to other fields. *Expert Systems with Applications, 119*, 456-475. https://doi.org/10.1016/j.eswa.2018.11.002

Frow, P., McColl-Kennedy, J. R., & Payne, A. (2016). Co-creation practices: Their role in shaping a health care ecosystem. *Industrial Marketing Management, 56*, 24-39.

Frow, P., Nenonen, S., Payne, A., & Storbacka, K. (2015). Managing co-creation design: A strategic approach to innovation. *British Journal of Management, 26*(3), 463-483.

Galbraith, J. R. (1973). *Designing complex organizations*. Addison-Wesley Longman Publishing Co., Inc.

Galvagno, M., & Dalli, D. (2014). Theory of value co-creation: a systematic literature review. *Managing Service Quality, 24*(6), 643-683.

Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management, 35*(2), 137-144.

García, D. L., Nebot, À., & Vellido, A. (2017). Intelligent data analysis approaches to churn as a business problem: a survey. *Knowledge and Information Systems, 51*(3), 719-774.

Garnham, N. (2005). From cultural to creative industries: An analysis of the implications of the "creative industries" approach to arts and media policy making in the United Kingdom. *International journal of cultural policy, 11*(1), 15-29.

George, G., Haas, M. R., & Pentland, A. (2014). Big data and management. *Academy of Management Journal*.

Gergen, K. J. (2009). *Realities and relationships: Soundings in social construction*. Harvard university press.

Gibbert, M., Leibold, M., & Probst, G. (2002). Five styles of customer knowledge management, and how smart companies use them to create value. *European management journal, 20*(5), 459-469.

Gobble, M. M. (2015). From Customer Intelligence to Customer Intimacy. *Research-Technology Management, 58*(6), 56-61.

Grant, R. M. (1991). The resource-based theory of competitive advantage: implications for strategy formulation. *California management review, 33*(3), 114-135.

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal, 17*(S2), 109-122.

Grissemann, U. S., & Sauer, S. N. E. (2012). Customer co-creation of travel services: The role of company support and customer satisfaction with the co-creation performance. *Tourism Management, 33*(6), 1483-1492.

Grönroos, C., & Voima, P. (2013). Critical service logic: making sense of value creation and co-creation. *Journal of the Academy of Marketing Science, 41*(2), 133-150.

Guarda, T., Santos, M. F., Pinto, F., Silva, C., & Lourenço, J. (2012). A conceptual Framework for Marketing intelligence. *International Journal of e-Education, e-Business, e-Management and e-Learning, 2*(6), 455.

Gudfinnsson, K., Strand, M., & Berndtsson, M. (2015). Analyzing business intelligence maturity. *Journal of Decision Systems, 24*(1), 37-54.

Gulati, R. (2010). Inside Best Buy's Customer-Centric Strategy. *Harvard business review*.

Gustafsson, A., Kristensson, P., & Witell, L. (2012). Customer co-creation in service innovation: a matter of communication? *Journal of Service Management, 23*(3), 311-327.

Halvorsrud, R., Kvale, K., & Følstad, A. (2016). Improving service quality through customer journey analysis. *Journal of Service Theory and Practice*.

Han, H., Yonggang, W., Tat-Seng, C., & Xuelong, L. (2014). Toward Scalable Systems for Big Data Analytics: A Technology Tutorial. *IEEE Access, 2*, 652-687. https://doi.org/10.1109/access.2014.2332453

Haugstvedt, A.-C., & Krogstie, J. (2012). Mobile augmented reality for cultural heritage: A technology acceptance study. *2012 IEEE international Symposium on Mixed and Augmented Reality (ISMAR)*, 247-255.

Heaton, J. (1998). Secondary analysis of qualitative data. *Social research update, 22*(4), 88-93.

Heidenreich, S., Wittkowski, K., Handrich, M., & Falk, T. (2015). The dark side of customer co-creation: exploring the consequences of failed co-created services. *Journal of the Academy of Marketing Science, 43*(3), 279-296.

Heiens, R. A., & Pleshko, L. P. (2011). A contingency theory approach to market orientation and related marketing strategy concepts: does fit relate to profit performance? *Management and Marketing, 6*(1), 19.

Hofacker, C. F., Malthouse, E. C., & Sultan, F. (2016a). Big data and consumer behavior: Imminent opportunities. *Journal of Consumer Marketing*.

Hofacker, C. F., Malthouse, E. C., & Sultan, F. (2016b). Big data and consumer behavior: Imminent opportunities. *Journal of Consumer Marketing, 33*(2), 89-97.

Hollebeek, L. D., Srivastava, R. K., & Chen, T. (2019). SD logic–informed customer engagement: integrative framework, revised fundamental propositions, and application to CRM. *Journal of the Academy of Marketing Science, 47*(1), 161-185.

Holmlund, M., Van Vaerenbergh, Y., Ciuchita, R., Ravald, A., Sarantopoulos, P., Ordenes, F. V., & Zaki, M. (2020). Customer experience management in the age of big data analytics: A strategic framework. *Journal of Business Research*.

Hong, T., & Kim, E. (2012). Segmenting customers in online stores based on factors that affect the customer's intention to purchase. *Expert Systems with Applications, 39*(2), 2127-2131.

Hosseini, S. M. S., Maleki, A., & Gholamian, M. R. (2010). Cluster analysis using data mining approach to develop CRM methodology to assess the customer loyalty.

Expert Systems with Applications, 37(7), 5259-5264. https://doi.org/10.1016/j.eswa.2009.12.070

Hu, H., Wen, Y., Chua, T.-S., & Li, X. (2014). Toward scalable systems for big data analytics: A technology tutorial. *IEEE Access, 2*, 652-687.

Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research, 21*(2), 155-172.

Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30-50.

Huster, M. J. C. I. M. (2005). Marketing intelligence: a first mover advantage. *8*(2), 13-17.

Iglesias, O., Markovic, S., Bagherzadeh, M., & Singh, J. J. (2018). Co-creation: A key link between corporate social responsibility, customer trust, and customer loyalty. *Journal of Business Ethics*, 1-16.

Im, J., & Qu, H. (2017). Drivers and resources of customer co-creation: A scenario-based case in the restaurant industry. *International Journal of Hospitality Management, 64*, 31-40.

Jafari, A., Taheri, B., & Vom Lehn, D. (2013). Cultural consumption, interactive sociality, and the museum. *Journal of marketing management, 29*(15-16), 1729-1752.

Jagadish, H. V. (2015). Big data and science: Myths and reality. *Big Data Research, 2*(2), 49-52.

Janssen, M., van der Voort, H., & Wahyudi, A. (2017). Factors influencing big data decision-making quality. *Journal of Business Research, 70*, 338-345.

Jouny-Rivier, E., Reynoso, J., & Edvardsson, B. (2017). Determinants of services co-creation with business customers. *Journal of Services Marketing, 31*(2), 85-103.

Katz-Gerro, T. (2004). Cultural consumption research: review of methodology, theory, and consequence. *International Review of Sociology, 14*(1), 11-29.

Keskin, H. (2006). Market orientation, learning orientation, and innovation capabilities in SMEs. *European Journal of innovation management.*

Khan, Z., & Vorley, T. (2017). Big data text analytics: an enabler of knowledge management. *Journal of knowledge management, 21*(1), 18-34.

Kozinets, R. V. (2002). The field behind the screen: Using netnography for marketing research in online communities. *Journal of marketing research, 39*(1), 61-72.

Kozlenkova, I. V., Samaha, S. A., & Palmatier, R. W. (2014). Resource-based theory in marketing. *Journal of the Academy of Marketing Science, 42*(1), 1-21.

Kumar, A., Niu, F., & Ré, C. (2013). Hazy: making it easier to build and maintain big-data analytics. *Communications of the ACM, 56*(3), 40-49.

L. Rodner, V., & Kerrigan, F. (2014). The art of branding– lessons from visual artists. *Arts Marketing: An International Journal, 4*(1/2), 101-118.

Lafrenière, D. (2020). Digital transformation: start with the customer, not IT! *Les Affaires*.

Latinovic, Z., & Chatterjee, S. C. (2019). Customer Centricity in the Digital Age. *MIT Sloan Management Review*.

Lau, R. Y. K., Li, C., & Liao, S. S. Y. (2014). Social analytics: Learning fuzzy product ontologies for aspect-oriented sentiment analysis. *Decision Support Systems, 65*, 80-94. https://doi.org/10.1016/j.dss.2014.05.005

Lau, R. Y. K., Zhao, J. L., Chen, G., & Guo, X. (2016). Big data commerce. *Information & Management, 53*(8), 929-933. https://doi.org/10.1016/j.im.2016.07.008

Laud, G., & Karpen, I. O. (2017). Value co-creation behaviour–Role of embeddedness and outcome considerations. *Journal of Service Theory and Practice, 27*(4), 778-807.

Lauterborn, B. (1990). New marketing litany: four Ps passé: C-words take over.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review, 52*(2), 21.

Lawrence, P. R., & Lorsch, J. W. (1967). Organization and environment.

Lee, H. K. (2005). When arts met marketing. *International journal of cultural policy, 11*(3), 289-305.

Lee, J. W., & Lee, S. H. (2017). Marketing from the Art World: A Critical Review of American Research in Arts Marketing. *The Journal of Arts Management, Law, and Society, 47*(1), 17-33.

Leeflang, P. S., Verhoef, P. C., Dahlström, P., & Freundt, T. (2014). Challenges and solutions for marketing in a digital era. *European management journal, 32*(1), 1-12.

Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing, 80*(6), 69-96.

Lenka, S., Parida, V., & Wincent, J. (2017). Digitalization capabilities as enablers of value co-creation in servitizing firms. *Psychology & Marketing, 34*(1), 92-100.

Leticia Santos-Vijande, M., González-Mieres, C., & Angel Lopez-Sanchez, J. (2013). An assessment of innovativeness in KIBS: Implications on KIBS'co-creation culture, innovation capability, and performance. *Journal of Business & Industrial Marketing, 28*(2), 86-102.

Levy, Y., & Ellis, T. J. (2006). A systems approach to conduct an effective literature review in support of information systems research. *Informing Science, 9*.

Lewrick, M., Omar, M., & Williams Jr, R. L. (2011). Market orientation and innovators' success: An exploration of the influence of customer and competitor orientation. *Journal of technology management & innovation, 6*(3), 48-62.

Li, Y.-M., & Li, T.-Y. (2013). Deriving market intelligence from microblogs. *Decision Support Systems, 55*(1), 206-217. https://doi.org/10.1016/j.dss.2013.01.023

Liang, T.-P., & Liu, Y.-H. (2018). Research Landscape of Business Intelligence and Big Data analytics: A bibliometrics study. *Expert Systems with Applications*.

Libert, B., Wind, Y. J., & Beck, M. (2015). What Apple, Lending Club, and AirBnB Know About Collaborating with Customers. *Havard Business Review*.

Lies, J. (2019). Marketing Intelligence and Big Data: Digital Marketing Techniques on their Way to Becoming Social Engineering Techniques in Marketing. *International Journal of Interactive Multimedia & Artificial Intelligence, 5*(5).

Lim, C., & Maglio, P. P. (2018). Data-driven understanding of smart service systems through text mining. *Service Science, 10*(2), 154-180.

Lincoln, Y. S. (2001). Engaging sympathies: Relationships between action research and social constructivism. *Handbook of action research: Participative inquiry and practice*, 124-132.

Liu, K., & Shi, J. (2015). A systematic approach for business data analytics with a real case study. *International Journal of Business Analytics, 2*(4), 23-44.

López-Robles, J.-R., Otegi-Olaso, J.-R., Gómez, I. P., & Cobo, M.-J. (2019). 30 years of intelligence models in management and business: A bibliometric review. *International Journal of Information Management, 48*, 22-38.

Lu, J., Cairns, L., & Smith, L. (2020). Data science in the business environment: customer analytics case studies in SMEs. *Journal of Modelling in Management*.

Lusch, R. F., & Nambisan, S. (2015). Service innovation: A service-dominant logic perspective. *MIS Quarterly, 39*(1).

Lusch, R. F., & Vargo, S. L. (2006). Service-dominant logic: reactions, reflections and refinements. *Marketing theory, 6*(3), 281-288.

Lusch, R. F., Vargo, S. L., & Wessels, G. (2008). Toward a conceptual foundation for service science: Contributions from service-dominant logic. *IBM systems journal, 47*(1), 5-14.

Maechler, N., Neher, K., & Park, R. (2016). From touchpoints to journeys: Seeing the world as customers do. *Retrieved March, 18*, 2017.

Maglio, P. P., & Spohrer, J. (2013). A service science perspective on business model innovation. *Industrial Marketing Management, 42*(5), 665-670.

Magnusson, P., Westjohn, S. A., Semenov, A. V., Randrianasolo, A. A., & Zdravkovic, S. (2013). The role of cultural intelligence in marketing adaptation and export performance. *Journal of International Marketing, 21*(4), 44-61.

Maguire, M., & Delahunt, B. (2017). Doing a thematic analysis: A practical, step-by-step guide for learning and teaching scholars. *All Ireland Journal of Higher Education, 9*(3).

Martini, A., Massa, S., & Testa, S. (2014). Customer co-creation projects and social media: The case of Barilla of Italy. *Business Horizons, 57*(3), 425-434.

McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D., & Barton, D. (2012). Big data: the management revolution. *Harvard business review, 90*(10), 60-68.

McCaslin, M. L., & Scott, K. W. (2003). The five-question method for framing a qualitative research study. *The qualitative report, 8*(3), 447-461.

McGrath, R. G., & McManus, R. (2020). Discovery-Driven Digital Transformation. *Harvard business review*.

Medina-Borja, A. (2015). Editorial Column—Smart Things as Service Providers: A Call for Convergence of Disciplines to Build a Research Agenda for the Service Systems of the Future. *Service Science, 7*(1), ii-v. https://doi.org/10.1287/serv.2014.0090

Melton, H., & Hartline, M. D. (2015). Customer and employee co-creation of radical service innovations. *Journal of Services Marketing, 29*(2), 112-123.

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management, 57*(2), 103169.

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Mikalef, P., Pappas, I. O., Krogstie, J., & Pavlou, P. A. (2020, 2020/01/01/). Big data and business analytics: A research agenda for realizing business value. *Information & Management, 57*(1), 103237. https://doi.org/https://doi.org/10.1016/j.im.2019.103237

Moges, H.-T., Dejaeger, K., Lemahieu, W., & Baesens, B. (2013). A multidimensional analysis of data quality for credit risk management: New insights and challenges. *Information & Management, 50*(1), 43-58.

Moreno, A., Valls, A., Isern, D., Marin, L., & Borràs, J. (2013). Sigtur/e-destination: ontology-based personalized recommendation of tourism and leisure activities. *Engineering Applications of Artificial Intelligence, 26*(1), 633-651.

Nakajima, S. (2012). Prosumption in Art. *American Behavioral Scientist, 56*(4), 550-569. https://doi.org/10.1177/0002764211429358

Nambisan, S. (2010). Virtual customer environments: IT-enabled customer co-innovation and value co-creation. In *Information technology and product development* (pp. 109-127). Springer.

Navarro-García, A., Peris-Oritz, M., Barrera-Barrera, R. J. J. o. B., & Marketing, I. (2016). Market intelligence effect on perceived psychic distance, strategic behaviours and export performance in industrial SMEs. *31*(3), 365-380.

Neuendorf, K. A., & Kumar, A. (2015). Content analysis. *The international encyclopedia of political communication*, 1-10.

Newman, D. (2018). 6 Digital Transformation Mistakes To Avoid. *Forbes*.

Ngai, E. W. T., Xiu, L., & Chau, D. C. K. (2009). Application of data mining techniques in customer relationship management: A literature review and classification. *Expert Systems with Applications, 36*(2), 2592-2602. https://doi.org/10.1016/j.eswa.2008.02.021

Nonaka, I. (1994). A dynamic theory of organizational knowledge creation. *Organization science, 5*(1), 14-37.

Nuovo, F. (2020). *COVID-19 : d'ici le déconfinement et la découverte d'un vaccin, il faut réinventer la culture*. Radio-Canada. https://ici.radio-canada.ca/premiere/emissions/dessine-moi-un-dimanche/segments/entrevue/166007/frulla-beaudoin-milieu-culturel-coronavirus

O'leary, Z. (2004). *The essential guide to doing research*. Sage.

O'Connor, C., & Kelly, S. (2017). Facilitating knowledge management through filtered big data: SME competitiveness in an agri-food sector. *Journal of knowledge management*.

OECD. (2020). *Enterprises by business size*.

Oertzen, A.-S., Odekerken-Schröder, G., Brax, S. A., & Mager, B. (2018). Co-creating services—conceptual clarification, forms and outcomes. *Journal of Service Management, 29*(4), 641-679.

OHern, M. S., & Rindfleisch, A. (2010). Customer co-creation. In *Review of marketing research* (pp. 84-106). Emerald Group Publishing Limited.

Okoli, C., & Schabram, K. (2010). A guide to conducting a systematic literature review of information systems research.

Onwuegbuzie, A. J., & Leech, N. L. (2007). A call for qualitative power analyses. *Quality & Quantity, 41*(1), 105-121.

Opresnik, D., & Taisch, M. (2015). The value of big data in servitization. *International Journal of Production Economics, 165*, 174-184.

Paarup Nielsen, A. (2006). Understanding dynamic capabilities through knowledge management. *Journal of knowledge management, 10*(4), 59-71.

Palys, T., & Atchison, C. (2012). Qualitative research in the digital era: Obstacles and opportunities. *International Journal of Qualitative Methods, 11*(4), 352-367.

Park, D. H., Kim, H. K., Choi, I. Y., & Kim, J. K. (2012). A literature review and classification of recommender systems research. *Expert Systems with Applications, 39*(11), 10059-10072. https://doi.org/10.1016/j.eswa.2012.02.038

Patton, M. Q. (1990). *Qualitative evaluation and research methods*. SAGE Publications, inc.

Payne, A., & Frow, P. (2005). A strategic framework for customer relationship management. *Journal of Marketing, 69*(4), 167-176.

Prabalad, C., & Hamel, G. (1990). The core competence of the corporation. *Harvard business review, 68*(3), 79-91.

Prahalad, C. K., & Ramaswamy, V. (2004). Co-creation experiences: The next practice in value creation. *Journal of interactive marketing, 18*(3), 5-14.

Preikschas, M. W., Cabanelas, P., Rüdiger, K., & Lampón, J. F. (2017). Value co-creation, dynamic capabilities and customer retention in industrial markets. *Journal of Business & Industrial Marketing, 32*(3), 409-420.

Qu, S. Q., & Dumay, J. (2011). The qualitative research interview. *Qualitative research in accounting & management*.

Quach, S., & Thaichon, P. (2017). From connoisseur luxury to mass luxury: Value co-creation and co-destruction in the online environment. *Journal of Business Research, 81*, 163-172.

Ragin, C. C. (2004). Turning the tables: how case-oriented research challenges. *Rethinking social inquiry: Diverse tools, shared standards, 123*.

Rakthin, S., Calantone, R. J., & Wang, J. F. (2016). Managing market intelligence: The comparative role of absorptive capacity and market orientation. *Journal of Business Research, 69*(12), 5569-5577.

Ramaswamy, V. (2009). Leading the transformation to co-creation of value. *Strategy & Leadership, 37*(2).

Ramaswamy, V., & Ozcan, K. (2014). *The co-creation paradigm*. Stanford University Press.

Ramaswamy, V., & Ozcan, K. (2016). Brand value co-creation in a digitalized world: An integrative framework and research implications. *International Journal of Research in Marketing, 33*(1), 93-106.

Ramaswamy, V., & Ozcan, K. (2018). What is co-creation? An interactional creation framework and its implications for value creation. *Journal of Business Research, 84*, 196-205.

Ramaswamy, V., & Ozcan, K. (2019). Digitalized Interactive Platforms: Turning Goods and Services into Retail Co-Creation Experiences. *NIM Marketing Intelligence Review, 11*(1), 18-23.

Ranjan, K. R., & Read, S. (2019). Bringing the individual into the co-creation of value. *Journal of Services Marketing*.

Ranoliya, B. R., Raghuwanshi, N., & Singh, S. (2017). Chatbot for university related FAQs. *2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, 1525-1530.

Rao, T. R., Mitra, P., Bhatt, R., & Goswami, A. (2018). The big data system, components, tools, and technologies: a survey. *Knowledge Information Systems Management*, 1-81.

Rao, T. R., Mitra, P., Bhatt, R., & Goswami, A. (2019). The big data system, components, tools, and technologies: a survey. *Knowledge and Information Systems, 60*(3), 1165-1245.

Rashid, Y., Waseem, A., Akbar, A. A., & Azam, F. (2019). Value co-creation and social media. *European Business Review, 31*, 761-784.

Rawson, A., Duncan, E., & Jones, C. (2013). The Truth About Customer Experience. *Harvard business review*.

Reijonen, H., & Laukkanen, T. (2010). Customer relationship oriented marketing practices in SMEs. *Marketing Intelligence & Planning*.

Reim, W., Sjödin, D. R., & Parida, V. (2019). Servitization of global service network actors–A contingency framework for matching challenges and strategies in service transition. *Journal of Business Research, 104*, 461-471.

Rentschler, R. (2002). Museum and performing arts marketing: The age of discovery. *The Journal of Arts Management, Law, Society, 32*(1), 7-14.

Roberts, N., Campbell, D. E., & Vijayasarathy, L. R. (2016). Using information systems to sense opportunities for innovation: Integrating postadoptive use behaviors with the dynamic managerial capability perspective. *Journal of Management Information Systems, 33*(1), 45-69.

Robson, C., & McCartan, K. (2016). *Real world research*. John Wiley & Sons.

Rowley, J. (2007). The wisdom hierarchy: representations of the DIKW hierarchy. *Journal of information Science, 33*(2), 163-180.

Rownd, M., & Heath, C. (2008). The American Marketing Association releases new definition for marketing. *Chicago, Il: AMA*.

Ruiz, J., Colbert, F., & Hinna, A. (2017). Arts and culture management. *Academila Revista Latinoamericana de Administración*.

Russo-Spena, T., & Mele, C. (2012). "Five Co-s" in innovating: a practice-based view. *Journal of Service Management, 23*(4), 527-553.

Rygielski, C., Wang, J.-C., & Yen, D. C. (2002). Data mining techniques for customer relationship management. *Technology in society, 24*(4), 483-502.

Saarijärvi, H., Kannan, P., & Kuusela, H. (2013). Value co-creation: theoretical approaches and practical implications. *European Business Review, 25*(1), 6-19.

Sahatiya, P. (2018). Big data analytics on social media data: a literature review. *International Research Journal of Engineering and Technology (IRJET) e-ISSN*, 2395-0056.

Samuel, A. (2015). Data is the next big thing in content marketing. *Harvard business review*.

Sassi, I. B., Mellouli, S., & Yahia, S. B. (2017). Context-aware recommender systems in mobile environment: On the road of future research. *Information Systems, 72*, 27-61.

Saura, J. R., Palacios-Marqués, D., & Ribeiro-Soriano, D. (2021). Digital marketing in SMEs via data-driven strategies: Reviewing the current state of research. *Journal of Small Business Management*, 1-36.

Saura, J. R., Palos-Sánchez, P., & Cerdá Suárez, L. M. (2017). Understanding the digital marketing environment with KPIs and web analytics. *Future Internet, 9*(4), 76.

Schafer, J. B., Frankowski, D., Herlocker, J., & Sen, S. (2007). Collaborative filtering recommender systems. In B. Peter, K. Alfred, & N. Wolfgang (Eds.), *The adaptive web* (pp. 291-324). Springer-Verlag.

Scholz, R. W., & Tietje, O. (2002). *Embedded case study methods: Integrating quantitative and qualitative knowledge*. Sage.

Schryen, G. (2015). Writing qualitative IS literature reviews—guidelines for synthesis, interpretation, and guidance of research. *Communications of the Association for Information Systems, 37*(1), 12.

Schwandt, T. A. (1994). Constructivist, interpretivist approaches to human inquiry. *Handbook of qualitative research, 1*, 118-137.

Selwood, S. (2001). The UK cultural sector. *London: Policy Studies Institute.*

Seng, J.-L., & Chen, T. C. (2010). An analytic approach to select data mining for business decision. *Expert Systems with Applications, 37*(12), 8042-8057. https://doi.org/10.1016/j.eswa.2010.05.083

Shamim, A., Ghazali, Z., & Albinsson, P. A. (2017). Construction and validation of customer value co-creation attitude scale. *Journal of Consumer Marketing, 34*(7), 591-602.

Sharma, G. (2017). Pros and cons of different sampling techniques. *International journal of applied research, 3*(7), 749-752.

Sharma, V. S., Mehra, R., Podder, S., & Burden, A. P. (2019). A journey towards providing intelligence and actionable insights to development teams in software delivery. *2019 34th IEEE/ACM International Conference on Automated Software Engineering (ASE)*, 1214-1215.

Shim, J., & Taylor, R. (2019). Purchase-Based Analytics and Big Data for Actionable Insights. *IT Professional, 21*(5), 48-56.

Sigala, M. (2011). eCRM 2.0 applications and trends: The use and perceptions of Greek tourism firms of social networks and intelligence. *Computers in Human Behavior, 27*(2), 655-661.

Siggelkow, N., & Terwiesch, C. (2019). The Age of Continuous Connection. *Harvard business review.*

Singh, P., & Verma, G. (2014). Mystery shopping: Measurement tool for customer intelligence management. *IOSR Journal of Business and Management Science, 16*(6), 101-104.

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research, 70*, 263-286. https://doi.org/10.1016/j.jbusres.2016.08.001

Söderlund, M. (2020). Employee encouragement of self-disclosure in the service encounter and its impact on customer satisfaction. *Journal of Retailing and Consumer Services, 53*, 102001.

Song, R., Moon, S., Chen, H., & Houston, M. B. (2018, May 01). When marketing strategy meets culture: the role of culture in product evaluations [journal article]. *Journal of the Academy of Marketing Science, 46*(3), 384-402. https://doi.org/10.1007/s11747-017-0525-x

Sorjonen, H., & Uusitalo, L. (2003). Market orientation and the programming of performing arts organisations. *AIMAC 7th International Conference on Arts and Cultural Management, 29*.

Spohrer, J., Maglio, P. P., Bailey, J., & Gruhl, D. (2007). Steps toward a science of service systems. *Computer, 40*(1), 71-77.

Spohrer, J. C., & Demirkan, H. (2015). Introduction to the smart service systems: Analytics, cognition, and innovation minitrack. *2015 48th Hawaii International Conference on System Sciences*, 1442-1442.

Stein, A., & Ramaseshan, B. (2016). Towards the identification of customer experience touch point elements. *Journal of Retailing and Consumer Services, 30*, 8-19.

Stone, M., Aravopoulou, E., Gerardi, G., Todeva, E., Weinzierl, L., Laughlin, P., & Stott, R. (2017). How platforms are transforming customer information management. *The Bottom Line, 30*(3).

Storbacka, K., Brodie, R. J., Böhmann, T., Maglio, P. P., & Nenonen, S. (2016). Actor engagement as a microfoundation for value co-creation. *Journal of Business Research, 69*(8), 3008-3017.

Sutcliff, M., Narsalay, R., & Sen, A. (2019). The Two Big Reasons That Digital Transformations Fail. *Harvard business review*.

Swami, D., & Sahoo, B. (2018). Storage size estimation for schemaless big data applications: A JSON-based overview. In *Intelligent Communication and Computational Technologies* (pp. 315-323). Springer.

Szirmai, A., & Verspagen, B. (2015). Manufacturing and economic growth in developing countries, 1950–2005. *Structural Change and Economic Dynamics, 34*, 46-59.

Tabrizi, B., Lam, E., Girard, K., & Irvin, V. (2019). Digital Transformation Is Not About Technology. *Harvard business review*.

Taghizadeh, S. K., Rahman, S. A., & Hossain, M. M. (2018). Knowledge from customer, for customer or about customer: which triggers innovation capability the most? *Journal of knowledge management*.

Tasic, J., Amir, S., Tan, J., & Khader, M. (2020). A multilevel framework to enhance organizational resilience. *Journal of Risk Research, 23*(6), 713-738.

Tellis, W. (1997). Introduction to case study. *The qualitative report, 269*.

Thornhill, A., Saunders, M., & Lewis, P. (2009). Research methods for business students. *Essex: Pearson Education Ltd*.

Tian, X. (2017). Big data and knowledge management: a case of déjà vu or back to the future? *Journal of knowledge management, 21*(1), 113-131.

Trim, P. R., & Lee, Y.-I. (2008). A strategic marketing intelligence and multi-organisational resilience framework. *European Journal of Marketing, 42*(7/8), 731-745.

Trischler, J., Pervan, S. J., & Scott, D. R. (2017). Exploring the "black box" of customer co-creation processes. *Journal of Services Marketing, 31*(3), 265-280.

Tscheu, F., & Buhalis, D. (2016). Augmented reality at cultural heritage sites. *Information and communication technologies in tourism 2016*, 607-619.

Tu, Y., Neuhofer, B., & Viglia, G. (2018). When co-creation pays: stimulating engagement to increase revenues. *International Journal of Contemporary Hospitality Management, 30*(4), 2093-2111.

Tuan, L. T., Rajendran, D., Rowley, C., & Khai, D. C. (2019). Customer value co-creation in the business-to-business tourism context: The roles of corporate social responsibility and customer empowering behaviors. *Journal of Hospitality and Tourism Management, 39*, 137-149.

UNESCO. (2020). *Policy guide for a resilient creative sector*.

Van Auken, S. (2015). From consumer panels to big data: An overview on marketing data development. *Journal of Marketing Analytics, 3*(1), 38-45.

Vargo, S. L., & Lusch, R. F. (2004). Evolving to a new dominant logic for marketing. In *The Service-Dominant Logic of Marketing* (pp. 21-46). Routledge.

Vargo, S. L., & Lusch, R. F. (2008). Service-dominant logic: continuing the evolution. *Journal of the Academy of Marketing Science, 36*(1), 1-10.

Vargo, S. L., & Lusch, R. F. (2016). Institutions and axioms: an extension and update of service-dominant logic. *Journal of the Academy of Marketing Science, 44*(1), 5-23.

Vargo, S. L., & Lusch, R. F. (2017). Service-dominant logic 2025. *International Journal of Research in Marketing, 34*(1), 46-67.

Vega-Vazquez, M., Revilla-Camacho, M. Á., & Cossío-Silva, F. J. (2013). The value co-creation process as a determinant of customer satisfaction. *Management Decision*.

Verhoef, P. C., & Lemon, K. N. (2013). Successful customer value management: Key lessons and emerging trends. *European management journal, 31*(1), 1-15.

Verleye, K. (2015). The co-creation experience from the customer perspective: its measurement and determinants. *Journal of Service Management, 26*(2), 321-342.

Verma, S. (2017). Big Data and Advance Analytics: Architecture, Techniques, Applications, and Challenges. *International Journal of Business Analytics, 4*(4), 21-47.

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-f., Dubey, R., & Childe, S. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research, 70*, 356-365.

Watkins, M. D. (2013). What Is Organizational Culture? And Why Should We Care? *Harvard business review*.

Webster, J., & Watson, R. T. (2002). Analyzing the past to prepare for the future: Writing a literature review. *MIS Quarterly*, xiii-xxiii.

Wedel, M., & Kannan, P. K. (2016). Marketing Analytics for Data-Rich Environments. *Journal of Marketing, 80*(6), 97-121. https://doi.org/10.1509/jm.15.0413

Weinberg, B. D., Davis, L., & Berger, P. D. (2013). Perspectives on big data. *Journal of Marketing Analytics, 1*(4), 187-201.

Werner, M. J. E., Yamada, A. P. L., Domingos, E. G. N., Leite, L. R., & Pereira, C. R. (2020). Exploring Organizational Resilience Through Key Performance Indicators. *Journal of Industrial and Production Engineering*, 1-15.

Whalen, P., Uslay, C., Pascal, V. J., Omura, G., McAuley, A., Kasouf, C. J., Jones, R., Hultman, C. M., Hills, G. E., & Hansen, D. J. (2016). Anatomy of competitive advantage: towards a contingency theory of entrepreneurial marketing. *Journal of Strategic Marketing, 24*(1), 5-19.

Willetts, M., Atkins, A. S., & Stanier, C. (2020). Barriers to SMEs adoption of big data analytics for competitive advantage. *2020 Fourth International Conference On Intelligent Computing in Data Sciences (ICDS)*, 1-8.

Williams, L. (2018). Help Your Team Measure Customer Experience Data More Accurately. *Harvard business review*.

Woo, J. Y., Bae, S. M., & Park, S. C. (2005). Visualization method for customer targeting using customer map. *Expert Systems with Applications, 28*(4), 763-772.

Wright, M., & Ashill, N. (1998). A contingency model of marketing information. *European Journal of Marketing*.

Wu, X., Zhu, X., Wu, G.-Q., & Ding, W. (2013). Data mining with big data. *IEEE transactions on knowledge data engineering, 26*(1), 97-107.

Xie, K., Wu, Y., Xiao, J., & Hu, Q. (2016). Value co-creation between firms and customers: The role of big data-based cooperative assets. *Information Management Science, 53*(8), 1034-1048.

Xu, Z., Frankwick, G. L., & Ramirez, E. (2016). Effects of big data analytics and traditional marketing analytics on new product success: A knowledge fusion perspective. *Journal of Business Research, 69*(5), 1562-1566.

Yan, Y., Huang, C., Wang, Q., & Hu, B. (2020). Data mining of customer choice behavior in internet of things within relationship network. *International Journal of Information Management, 50*, 566-574.

Yin, R. K. (1981). The case study crisis: Some answers. *Administrative Science Quarterly, 26*(1), 58-65.

Yin, R. K. (2003). Case study research: Design and methods (Vol. 5).

Yin, R. K. (2015). *Qualitative research from start to finish*. Guilford publications.

Yohn, D. L. (2018). 6 Ways to Build a Customer-Centric Culture. *Havard Business Review*.

Zerbino, P., Aloini, D., Dulmin, R., & Mininno, V. (2018). Big Data-enabled customer relationship management: A holistic approach. *Information Processing & Management, 54*(5), 818-846.

Zhang, H., Lu, Y., Wang, B., & Wu, S. (2015). The impacts of technological environments and co-creation experiences on customer participation. *Information & Management, 52*(4), 468-482.

Zhang, H.-R., & Min, F. (2016). Three-way recommender systems based on random forests. *Knowledge-Based Systems, 91*, 275-286.

Zhang, J. Z., Watson IV, G. F., & Palmatier, R. W. (2018). Customer Relationships Evolve-So Must Your CRM Strategy. *MIT Sloan Management Review, 59*(3), 1-7.

Zhang, T., Lu, C., Torres, E., & Chen, P.-J. (2018). Engaging customers in value co-creation or co-destruction online. *Journal of Services Marketing, 32*(1), 57-69.

Zhang, W., & Banerji, S. (2017). Challenges of servitization: A systematic literature review. *Industrial Marketing Management, 65*, 217-227.

Zhang, Y., & Wildemuth, B. M. (2009). Qualitative analysis of content. *Applications of social research methods to questions in information and library science, 308*, 319.

Zuberi, M. F., & Rajaratnam, D. (2020). Measuring retail performance in an omni-channel world. *Journal of Marketing Channels, 26*(2), 120-126.