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The Quest for Customer Intelligence to Support Marketing Decisions: A Knowledge-Based Framework

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The quest for customer intelligence to create value in marketing has highlighted the significance of the research focus of this paper. Customer intelligence, which is defined as understandings 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 paper has developed a framework of customer intelligence to support marketing decisions through the lens of knowledge-based theory. The proposed framework aims at supporting enterprises to identify the right customer data for the right customer intelligence corresponding with the right marketing decisions. In this light, 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 decisions to maximize value creation. To illustrate the framework, an example is presented. 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 decisions.

Keywords: Customer intelligence; knowledge base; marketing decisions; massive data.

AMS Subject Classification: 90B60, 90B50, 68U35

1. Introduction

In the era of the knowledge-based economy, customer intelligence plays a significant role in the survival and prosperity of enterprises.[1,2] Customers create a significant amount of data through interactions on digital platforms, which has become a valuable source of knowledge to improve marketing decisions related to products/services, pricing, promotion, and distribution.[3–5] 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.[6] The application of customer intelligence offers win–win solutions for both enterprises and customers.[5,7] Enterprises can improve their marketing and financial performance, whereas customers can increase their satisfaction and experience with products/services.[8,9]

However, enterprises find it defiant to take advantage of customer intelligence for marketing decisions. The first challenge arises from the changes in the concept of customer intelligence over the past 20 years due to the technological revolution in the era of massive data.[10,11] The technological revolution has led to changes in management strategies and the organizational structure.[3,12] The second challenge involves the identification of different types of customer intelligence.[4,13] 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 (SMEs). Lastly, the application of specific types of customer intelligence for relevant marketing decisions is not a trivial task.[14,15] The value of customer intelligence is amplified and leveraged only if enterprises can make use of it for marketing decisions.[16,17] These challenges prompt the motivation to study customer intelligence in the age of massive data and develop a framework to manage and leverage its value.

Building on these reflections, the research objective of this paper is to develop a knowledge-based framework of customer intelligence to support marketing decisions. The framework will serve as a kickoff for enterprises to acquire and apply customer intelligence to make data-driven decisions. To respond to the research objective, the following research questions (RQs) are explored:

RQ 1**:** *How does literature conceptually approach customer intelligence from the knowledge-based approach?*

RQ 2**:** *What are the specific applications of customer intelligence to support marketing solutions?*

To carry out this research, this paper adopted the exploratory research approach, which is defined as the process of investigating a problem that has not yet been studied or thoroughly investigated.[18] This paper uses the literature as existing resources on the subject under study. Consequently, the remaining structure of the paper continues with the literature review, which clarifies the research methodology and the revolution of customer intelligence. Then, the studies related to the knowledge-based theory are examined to set the foundation for the framework. Through the framework, the method to transform customer data into customer intelligence is presented. Based on the framework, the applications of customer intelligence to create value in marketing are clarified. Then, an example is presented to illustrate the proposed framework. The last section of the paper indicates an in-depth discussion of theoretical and practical contributions.

The previous version of this study has been published in the proceeding of the 13th Asian Conference on Intelligent Information and Database Systems (ACIIDS 2021) conference.[13] This paper is an extended version that is based on the knowledge-based approach to better clarify different levels of customer intelligence with relevance to data, information, knowledge, and insight. Compared to the conference version, this paper demystifies and explores the four types of customer intelligence, including product-aware intelligence, customer DNA intelligence, customer experience intelligence, and customer value intelligence. The study also makes a further step in identifying pertinent data mining methods and algorithms for the applications of different types of customer intelligence. Another important point to ponder is that the proposed framework is being experimented through the development of the customer intelligence application for SMEs.

2. Literature Review

2.1. *Research methodology*

To ensure a comprehensive review, the paper follows the systematic approach by Webster and Watson.[19] Searches are conducted in databases, including Scopus, Science Direct, Emerald Insight, SpringerLink, and ProQuest.[11,20] Different keywords such as "customer intelligence", "customer knowledge", "customer information", "customer insight", and "customer intimacy" are used to look for articles from these databases. As a synonym for "customer", the noun "consumer" is also used to combine with other words such as intelligence, knowledge, and insights to identify relevant articles.

Subsequently, inclusion and exclusion criteria are applied to filter out relevant articles. Assuming most studies on customer intelligence are written in English, only publications in this language are chosen. Articles that are not peer-reviewed are excluded. Finally, the selected literature is also chosen with relevance to massive data. This process ends with 65 most relevant articles. Figure 1 demonstrates the fluctuation of the research on this research topic from 2000 to 2020. As seen in Fig. 1, it is noted that the research topic on customer intelligence is catching more attention, particularly from 2014 to the present.

All selected articles are also grouped by journal titles. Table 1 summarizes the list of journals along with the number of selected articles. It can be seen that a significant

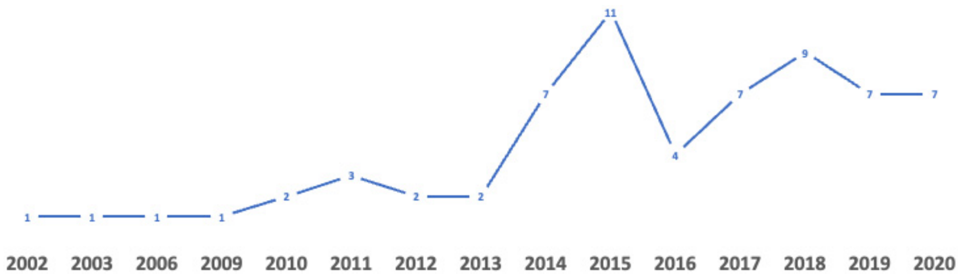

Fig. 1. Distribution of selected journals by year of publication.

proportion of selected articles comes from the Journal of Business Research (10.77%), Harvard Business Review (9.23%), and International Journal of Information Management (4.62%). Other journals, which are also well-referenced, are Expert Systems with Applications, MIS Quarterly, Journal of Marketing, and so on.

2.2. *Revolution of customer intelligence*

As mentioned above, the era of massive data has led to significant changes in the perspectives of management, organization, and technology in terms of customer intelligence.[9,20,21] The management dimension aims at applying customer intelligence to create value. The organizational dimension examines changes in organizational culture, structure, and business models to promote customer intelligence. The technological dimension focuses on information technology and analytic techniques to transform data into customer intelligence. To explore such a revolution, Table 2 summarizes research related to customer intelligence over the past 20 years.

The literature barely reveals an official definition of customer intelligence, particularly a definition that can comprehensively cover the three perspectives of management, organization, and technology.[5,22,23] Most studies spotlight the importance of the application of customer intelligence to support the management dimension with various streams, including customer target,[24] innovation,[25,26]

Table 1. Distribution of selected journals by journal titles.

Journal title	Number	Percentage
Journal of Business Research	7	10.77%
Harvard Business Review	6	9.23%
International Journal of Information Management	3	4.62%
Expert Systems with Applications	2	3.08%
Journal of Marketing	2	3.08%
Big Data Research	2	3.08%
MIS Quarterly	1	1,54%
Others	42	64.62%
Total	65	100.00%

Table 2. Synthesis and analysis of definitions of customer intelligence.

Article	Organization	Management	Technology
Rygielski *et al.*[24]		– Customer targeting – Product sales	– CRM
Chen and Popovich[21]	– Business process	– Customer behaviors	– CRM, ERP
Keskin[25]	– Organizational learning	– Innovation	
Lewrick *et al.*[26]		– Product innovation – Product development	
Guarda *et al.*[27]		– Customer service	– Data system
Singh and Verma[28]	– Business Process	– Customer experience – Customer behaviors	
Samuel[30]			– Social media data
Gobble[22]		– Customer relationships – Decision-making	
Rakthin *et al.*[23]		– Customer needs – Buying decision model	
Stone *et al.*[31]	– Human capital – Business process		– Social media data – Massive data
López-Robles *et al.*[29]		– Decision making	– Massive data
Yan *et al.*[5]		– Recommendations	– Internet of things – Massive data
Dam *et al.*[32]	– Customer-oriented culture – Staff engagement – Communication – Policy	– Customer relationship strategy – Sustainable Customer relationship – Recommendations	– Massive data – Customer analytics

customer service,[27] customer experience,[28] customer behaviors,[23,28] customer relationships,[22] decision-making,[29] and recommendations.[5]

Table 2 reveals that most definitions of customer intelligence focus on the organizational dimension. The studies by Keskin[25] and Singh and Verma[28] made a difference by highlighting the dimensions of organizational learning and the business process of customer intelligence. On the other side, the technological dimension has witnessed the revolution from traditional Enterprise Resource Planning (ERP), Customer Relationship Management (CRM) to massive data platforms and artificial intelligence (AI)-based solutions.[30,31] Customer intelligence is moving to a higher level due to the support of data mining techniques for the collaborative decision-making process.[22,29] Therefore, customer intelligence is capable of enhancing personalized customer experience through analytics and the excavation of massive data.[5]

As most definitions of customer intelligence are outdated in the context of the massive data revolution,[7,22,24] there is a need for an updated definition to adapt to these changes. In fact, the era of massive data has reshaped the definition of customer intelligence.[8,9] This study first relies on the definition of intelligence from the Oxford dictionary as the "ability to acquire and apply knowledge and skills."[33] To amplify the value of customer intelligence for marketing solutions, the authors also examine the role of marketing in "creating, communicating, delivering, and exchanging offerings."[34] According to the American Marketing Association (AMA), customers are "actual or prospective purchasers of products or services."[35] In the era of massive data, the proliferation of customer-generated data on digital platforms along with analytic techniques has changed the way that marketing acquires and applies knowledge and skills from customers.[8,9] Following this view, contemporary marketing relies on analytic techniques, including descriptive, predictive, prescriptive to transform data into intelligence.[20,36] Building on these reflections, this paper reshapes the definition of customer intelligence in the age of massive data as follows:

Customer intelligence is the ability to acquire knowledge and skills from massive data through customer analytics and then apply them to the process of creating, communicating, delivering, and co-creating to offer value.

3. Knowledge-Based Framework of Customer Intelligence for Marketing Value Creation

This section of the paper addresses the knowledge-based view,[37] which serves as an anchor for the development of the theoretical framework. With the purpose to synthesize and extend existing studies, the paper continues by proposing a theoretical framework for customer intelligence, which is based on theories to develop factors, constructs, variables, and their relationships.[19] In this paper, the theoretical framework is derived from the literature review and is based on the knowledge-based theory. As illustrated in Fig. 2, the framework clarifies customer data, customer information, and customer intelligence along with the value creation for marketing. The process to transform customer data into customer intelligence through different types of analytics is also presented.

3.1. *Knowledge-based theory*

This study lays its foundation on the knowledge-based theory[37] combined with the concept of the marketing mix.[38] The knowledge-based theory by Grant[37] 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.[37,39] Concerning customer intelligence from the viewpoint of the knowledge-based theory, customer intelligence can be perceived as explicit knowledge as it is structurally recorded and stored in databases. On the flip side, the experience and skills of managers and employees can be labeled as tacit knowledge. Customer intelligence will be implicit unless it is applied to develop rules, instructions, and procedures as directive tasks or marketing applications.[12,40] Therefore, the knowledge-based

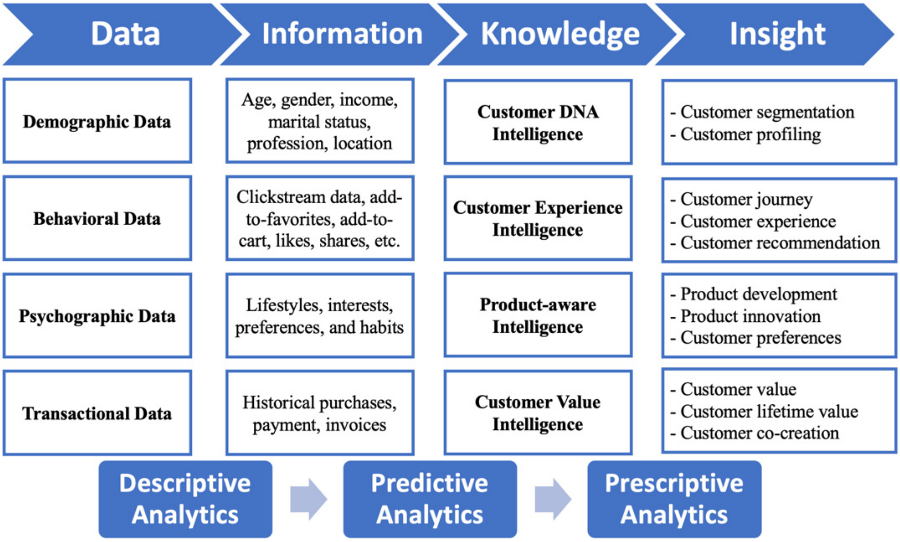

Fig. 2. Knowledge-based framework of customer intelligence for value creation in marketing.

theory[37] reinforces and extends the importance of customer intelligence as a key indicator to create competitive advantages for enterprises. From the perspective of marketing, the concept of the marketing mix[38] is then adopted to classify and clarify the specific types of knowledge or intelligence on markets, products, customers, and competitors for better application.

The knowledge development process, often called Data-Information-Knowledge-Wisdom (DIKW) hierarchy, starts with data, progresses into information, and reaches the highest level as wisdom. *Data* are raw and unprocessed numbers, symbols, signals, or text.[16,41] *Information* is the description of data to be useful, whereas *knowledge* provides instructions on the use of information based on the context. *Wisdom* is considered as the highest hierarchy of data transformation and is a huge challenge for enterprises to reach.[42] Therefore, this paper prefers to use the term "insight", which might be located in between knowledge and wisdom. *Insight* is the ability to perceive and apply *knowledge* to drive actions.[43] In this light, customer intelligence is the understanding of the application of knowledge relative to customers, which promotes data-driven decisions to optimize marketing solutions.

3.2. *From customer data to customer information: Descriptive analytics*

Based on the knowledge-based view,[37] customer intelligence starts with data. Through the prism of customer intelligence, customer data can be categorized into demographic, behavioral, transactional, and psychographic data.

Demographic data. Demographic data tell *Who* customers are.[11] Demographic data contain information related to age, gender, income, marital status, profession, and location.[11,16] Enterprises can acquire demographic data from the U.S Census Bureau, CRM systems, and social media.

Behavioral data. Behavioral data unveil *How* customers interacted on websites, mobile devices, and social media.[7,44] Examples of behavioral data are clickstream data, add-to-favorites, and add-to-cart.[20,45] Nowadays, executives consider customers' likes, shares, and comments on social media as an important source to provide a quick snapshot of customer behaviors.

Transactional data. Transactional data show *What* customers purchased.[4,8] Transaction data can be acquired from different sources such as transaction records, sales reports, billing records, and CRM systems.[10,20] Integrating and analyzing transactional data from various sources are crucial as they reflect the value of customers.[5,15]

Psychographic data. Psychographic data explain *Why* customers made a purchase.[8,46] Psychographic data are the integration of demographic, behavioral, and transactional data to discover the motivations and reasons for buying products and services.[45,47] The era of massive data also acknowledges the tendency of text mining on social media to acquire psychographic data.[32]

Descriptive analytics is often applied to explore historical data and transform them into information. Descriptive analytics techniques cover different techniques including business reporting, descriptive statistics, regression modeling, and visualization.[17] Business reporting involves the process of generating standard reports, ad hoc reports, query/drill down, and alerts.[10,20] Executives rely on data mining techniques such as association, clustering, regression, decision trees, etc. to analyze business reports. Regression is the most well known to find out trends of customers from past data.[10,41] *Descriptive analytics* puts trust in visualization techniques to better communicate the results of descriptive analytics.[48]

3.3. *From customer information to customer knowledge: Predictive and prescriptive analytics*

Predictive and prescriptive analytics are applied to transform customer information into customer intelligence, which is the focus of this study at the knowledge level. As the nature of *predictive analytics* is to forecast future possibilities, it would make information more actionable.[10] Predictive analytics relies on quantitative techniques such as statistic modeling, regression, and machine learning techniques to predict the future.[16,17] Accordingly, linear regression techniques and statistic modeling are conducted to explore interdependencies among variables and make predictions concerning customer behaviors and preferences.[10,47] Different machine learning techniques such as neural network algorithms, self-organizing maps provide insights and future outcomes on customers.[10,41]

On the other hand, *prescriptive analytics* aims at converting customer information into customer intelligence to optimize business decisions.[5,16]

As recommendation-focused analytics, prescriptive analytics ensures the efficiency of customer insights.[17,47] In this vein, optimization and simulation are applied to gain insights on customers for complex business situations. The simulation focuses on handling complex problems, whereas optimization provides the most optimal solutions considering certain constraints.[11,49]

Once information is transformed into intelligence through the application of predictive and prescriptive analytics, the paper classifies customer intelligence based on the knowledge-based view[37] combined with the concept of the marketing mix.[38] Accordingly, this research proposes four types of customer intelligence including product-aware intelligence (know-what), customer DNA intelligence (know-who), customer experience intelligence (know-how), and customer value intelligence (know-why).

Product-aware intelligence. Product-aware intelligence demystifies *what* customers like and develops products/services based on their needs.[17,50] 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.[51,52] Acquiring user-generated content and web content allows enterprises to develop product/service solutions to deliver value for customers.[53,54] 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 for customers.[22,55]

Customer DNA intelligence. Customer DNA intelligence aims at identifying, targeting, and positioning customers for personalized services.[56,57] Based on customer DNA intelligence, enterprises can divide a business market into subgroups of customers with similar characteristics and develop into customer profiles.[45,49] Customer profiles provide the breakdown of demographic information such as age, gender, marital status, household income, and occupation.[5,58] 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.[4,5,24]

Customer experience intelligence. 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.[9,44] Customer experience intelligence also demystifies value, resources, and engagement forms to facilitate *customer co-creation*.[14,59] 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.[16,54]

Customer value intelligence. Customer value intelligence works toward maximizing customer value for enterprises. Literature categorizes customer value into economic, social, and cognitive values.[54,60] 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.[61] 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.[51,62] Finally, customer co-creation value makes sense of relevant value, resources, and engagement forms to encourage them to co-create value.

4. Applications of Customer Intelligence for Value Creation in Marketing

This part continues with the application of customer intelligence to create value in marketing. Figure 3 presents the data mining methods and algorithms relevant to specific applications of customer intelligence. There are six typical data mining methods that extract customer intelligence for various applications as follows[1,47,61]:

The classification method determines and predicts attributes of clusters such as customers or products.[8,11] 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.[5,61] 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.[5,24] In clustering, different techniques that 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.[63,64] The most often used regression techniques are linear regression and logistic regression.

The prediction method estimates and foresees future behaviors and values based on historical records.[20,47] Typical prediction methods are logistic model prediction, neural networks, and survival analysis.

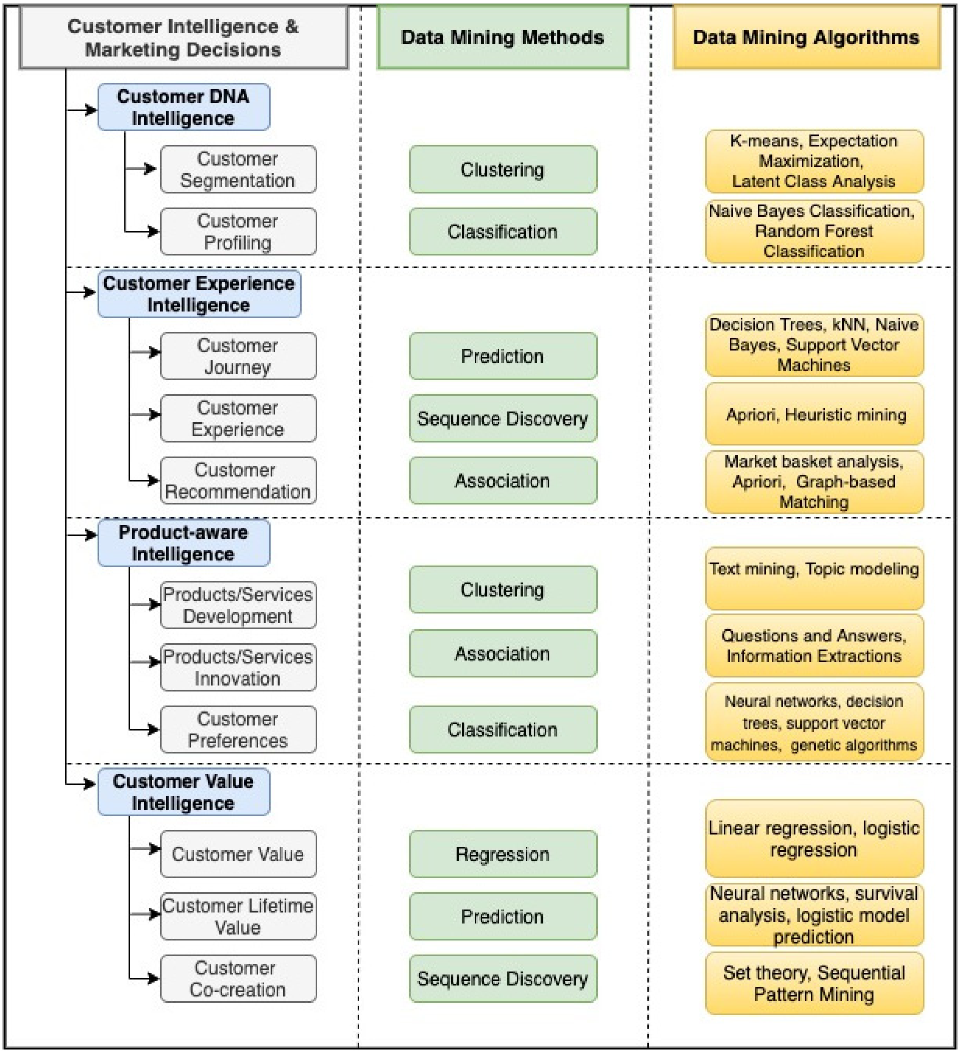

Fig. 3. Data mining methods and techniques related to customer intelligence.

The sequence discovery method identifies hidden patterns and describes orders of behaviors in sequential data.[5,63] Common sequence discovery techniques are set theory and sequential pattern mining.

4.1. *Product-aware intelligence*

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.[45] Therefore, enterprises are under pressure for the development and innovation of products and services.[65,66]

Customer product/service development. The application of customer intelligence in service and product development would yield profitable outcomes.[16,56] It keeps track of changes in markets and customer preferences as it is extracted from customer interactions on digital platforms.[23,62] 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.[28,45]

Customer product/service innovation. Customers can involve as co-ideators for product/service innovation.[65,66] In fact, customers with product/service interests and passions often participate in the process of idea generation for the product/service conceptualization and improvement.[60,67] The interaction between an enterprise and customers facilitates improvement for existing products/services and gradually stimulates ideas for product/service innovation.[7]

Customer preferences. Product-aware intelligence measures the overall emotion of customers towards products/services and verifies if products/services can meet customer expectations.[8,17] Understanding customer preferences is significant in responding to customer needs and developing promotional strategies and tactics.[3,4]

4.2. *Customer DNA intelligence*

Customer DNA intelligence identifies who customers are. Therefore, this type of intelligence can support enterprises with customer segmentation and customer profiling.

Customer segmentation. Customer identification focuses on how to identify the most profitable customers.[45,49] In fact, it is challenging to identify the most lucrative customer segments due to the huge volume and variety of massive data. Customer intelligence is applied to identify customer segments with similar interests and profitability.[11,61] Various demographic, psychographic, behavioral, or geographic criteria are used for segmentation.[11,24] Customer segmentation divides customers into homogenous segments and builds customer profiles.[45,49]

Customer profiling. Customer profiles contain information on demography, buying behaviors, purchasing attributes, product category, and estimated customer lifetime value.[8,11] Due to customer intelligence, enterprises can implement different data mining techniques related to target customer analysis to choose the most profitable segment.[45,61] Enterprises rely on customer profiling to develop marketing campaigns and maintain a long-term relationship with customers.[56,68]

4.3. *Customer experience intelligence*

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. 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.[69] In other words, the three stages represent the pre-purchase, purchase, and post-purchase of a customer journey.[44] Accordingly, service providers attempt to map customer journeys with key touchpoints in each stage.[70,71]

Customer experience. Customer experience catches the attention of researchers and practitioners as it reflects the extent of how customers engage with products.[8,65] Customer intelligence is capable of enhancing personalized customer experience through analytics and excavation of massive data.[5] In particular, analyzing customer-generated contextual data is significant to manage customer experience and to reinvent customer journeys from pre-purchases to post-purchases.[44,68] Furthermore, integrating and interpreting different sources of customer data to help enterprises identify and prioritize key customer journeys to optimize the customer experience.[9]

Product/service recommendation. The application of customer intelligence in recommender systems promotes the optimization of customer experience by engaging customers with product/service recommendations.[5,72] 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.[7]

4.4. *Customer value intelligence*

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 value. 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.[60,62] In the era of massive data, knowledge and skills from customers are considered more significant as they are a great source for customer intelligence.

Customer lifetime value. Customer lifetime value is a prediction of the total monetary value that customers are expected to spend for an enterprise during their lifetime.[61] With the support of customer intelligence, service providers will have sufficient data and information to estimate customer lifetime value.[5,61] Therefore, they can fine-tune their marketing strategies, particularly strategies related to STP, for optimal outcomes.[4,5,24]

Customer co-creation. Customer co-creation is described as the joint creation of value by the service providers and customers through the mutual application of operant resources.[60,67] From the standpoint of service providers, customer value co-creation provides a significant source of customer data for product and service innovation.[7] From the perspective of customers, customer value co-creation improves customer experiences and knowledge.[59]

5. Illustrative Example of the Customer Intelligence Framework

Figure 4 presents an illustrative example of the customer intelligence application pertaining to service offerings for SMEs, called the CIA-SME system, including four levels: data, information, knowledge, and insight levels. The CIA-SME system functions as a service system, which is defined as the "configuration of people, technologies, and shared knowledge" to turn resources into value propositions.[73] This is our ongoing project that aims at developing an open-source system to promote customer intelligence in SMEs. The system architecture, data sources,

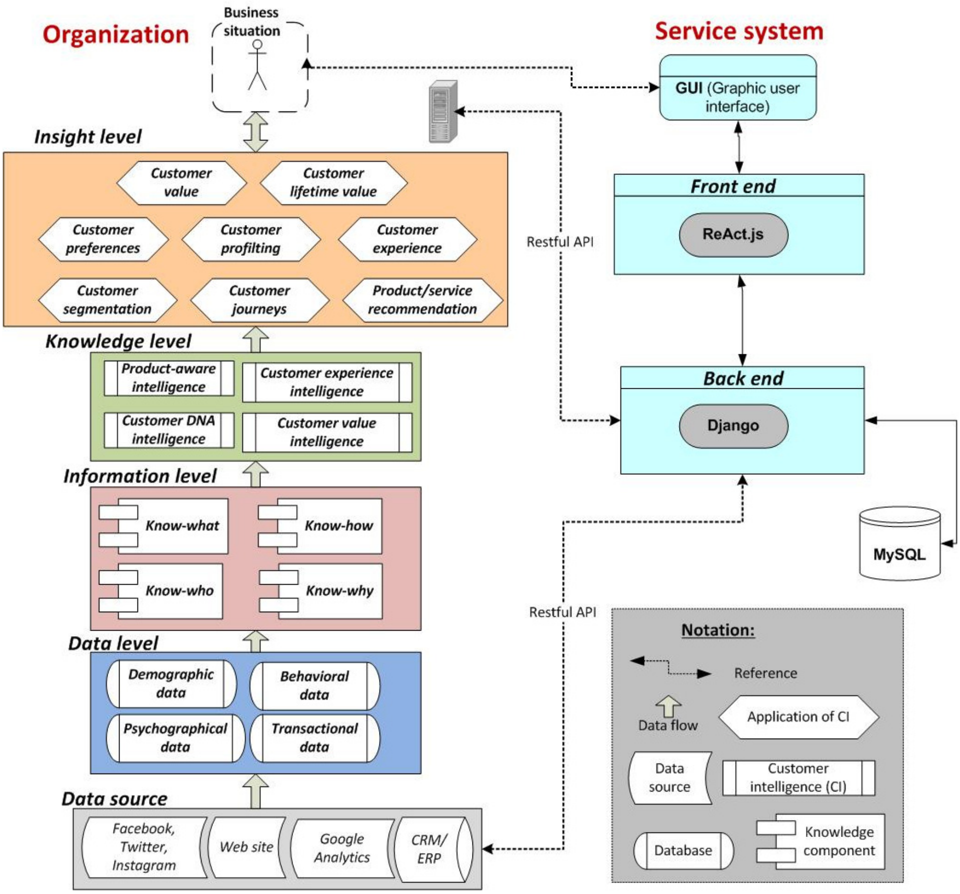

Fig. 4. Customer intelligence application for SMEs.

knowledge components, and types of customer intelligence have been examined and selected based on the characteristics of SMEs.

System architecture. Concerning the backend, the CIA-SME system is based on the Django framework, a Python-based free and open-source web framework, which follows the model–template–view architectural pattern.[a] The Python language has been selected because of its capability for data science and machine learning. MySQL,[b] which is open-source relational database management, has been used to store the data repositories. Concerning the frontend, the CIA-SME system uses React,[c] which is also a free and open-source front-end JavaScript library for building user interfaces based on UI components. The business users can use the services of the system via its graphic user interface (GUI) that covers the data-as-a-Service, information-as-a-Service, knowledge-as-a-Service, and insight-as-a-Service.[12] To integrate with other existing systems, those services are also available via Restful APIs.

Data level. The data level of the CIA-SME focuses on four types of data. Firstly, the *demographic data* related to customers are obtained mostly from Google Analytics[d] via its services such as Google Big Query and Google Analytics Query Explorer. Secondly, the *behavioral data* are extracted based on the interaction between customers and social networks (including Facebook, Instagram, and Twitter) or websites. Thirdly, the *transactional data* are imported from CRM or ERP systems. Finally, the *psychographic data* can be obtained by sentiment analysis of data related to products/services from social networks.

Information level. The information level covers the knowledge components such as know-who, know-what, know-how, and know-why.[74] *Know-who* concerns the classes representing the stakeholders of the value creation network such as users, individuals, organizations, and customers. *Know-what* deals with business objects such as classes for representing products and services. *Know-how* interests in business activities performed on business objects such as the classes for sessions, interactions, journeys, web activities, and transactions, and *Know-why* underlines the interrelationship between the other knowledge components relevant to classes and represents the relation between business objects/business activities and location/time frame.

Knowledge level. The knowledge level covers all four types of customer intelligence. *Product-aware intelligence* mostly focuses on the analysis of social networks and web activities to determine customers' expectations and preferences. *Customer DNA intelligence* concerns the customer profiles and customer segmentations. *Customer experience intelligence* deals with customer journey management, customer experience optimization, and product recommendations. Finally, *customer value intelligence* concentrates on customer value and how to reach customer lifetime value.

[a] www.djangoproject.com.
[b] www.mysql.com.
[c] www.reactjs.org.
[d] analytics.google.com.

Insight level. The insight level focuses on how to turn customer insights into business value. The customer insights provided by the CIA-SME system can be consumed as insight-a-as-a-Service, directly via the GUI or indirectly via the APIs. Depending on the type of insights and the business situation as the input, the output of the service can be an interactive dashboard, scorecard, prevision, recommendations, suggested actions, and decision-support.

6. Conclusion

The quest for customer intelligence to create value in marketing has highlighted the significance of the research focus of the paper. In this light, the paper has developed a framework of customer intelligence to support marketing decisions through the lens of the knowledge-based theory. The proposed framework demystifies specific types of customer data, customer information, and customer intelligence along with relevant analytic techniques to transform customer data into customer intelligence. Accordingly, the applications of customer intelligence are clarified with relevant marketing decisions to create value.

Considering the lack of literature for a relevant framework, this paper responds to such a challenge to transform and leverage the value of customer data for customer intelligence. Compared to previous frameworks on customer intelligence, the proposed framework is promised to outperform as it examines changes in the age of massive data with the focus on marketing decisions to create value. In comparison with the related work, most researches on customer intelligence tend to focus on product/service development instead of providing multifaced aspects of its applications.[75] Therefore, enterprises seem to apply customer intelligence to produce one-off products/services. The literature shows that previous models give prominence to a specific application of customer intelligence. For example, the customer intelligence model by Maehler *et al.*[40] makes a great emphasis on innovation. Consequently, the importance and originality of this study are that it covers multifaced aspects of marketing decisions such as customer segmentation, products/services development, customer experience, customer co-creation, and so on.

Regarding theoretical contributions, a comprehensive review of customer intelligence over the past 20 years was conducted to reveal the revolution in this research stream. Accordingly, the paper proposed a revised definition of customer intelligence with modifications from massive data. The paper has also enriched the literature by exploring different aspects of customer intelligence from the perspectives of management, organization, and technology. Furthermore, the knowledge-based framework of customer intelligence has made a significant theoretical contribution by bridging the gap between knowledge management and marketing. The framework is promised to be a source of reference for both practitioners and researchers to further their studies.

In terms of practical contributions, this paper sheds light on the complex nature of customer intelligence in the era of massive data. Considering such complexity, the proposed framework 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 framework can serve as a roadmap for enterprises to avoid losing track of creating value from customer intelligence. Enterprises can confide in the framework to determine relevant types of customer intelligence that match their analytic capabilities and strategic objectives.

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