Artificial Intelligence Marketing for Customer-Relationships

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Artificial intelligence marketing (AIM), which is an interdisciplinary research topic, is a disruptive technology that enables machines to automate the process of collecting and processing a massive amount of data and information to create knowledge related to marketing mix. This capability is essential to manifest personalization at scale, which has been impossible through human effort alone. This paper synthesizes the literature and develops an AIM framework to create a quantum leap in customer relationship enhancement, including customer trust, satisfaction, commitment, engagement, and loyalty.

Keywords: artificial intelligence marketing ; artificial intelligence ; marketing ; customer relationship ; consumer trust ; customer satisfaction ; customer commitment ; customer engagement ; customer loyalty

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1. Introduction

Generally speaking, traditional marketing approaches focus on firm-level achievements, such as identifying competitive advantages and improving financial gains. Of particular interest is the capability of traditional marketing to enhance customer relationship. Although "building deeper understanding, relationships, and offerings to individual customers" [1] is important, traditional marketing tends to know the purchase point only and miss each and every single individual customer's detail and touch point. In other words, traditional marketing does not scale well and is unable to consider all instances when a customer encounters the brand or its offerings. Most importantly, the comprehensiveness of customer relationship, which includes customer trust, satisfaction, commitment, engagement, and loyalty, has made traditional marketing far from being effective to improve customer relationship, and this warrants the need for AI to bridge the gap.

Artificial intelligence marketing (AIM) uses AI to automate the curation of a massive amount of data and information related to marketing mix in order to create knowledge. Subsequently, AIM uses the knowledge to perform and automate marketing processes, such as generating market intelligence [2]. Such capability enables AIM to go the extra length to manifest personalization [3] for each customer to understand his/her needs and wants, allowing such impossible features in the past to become possible now. For comparison, AIM can drill down to the individual customer level across various activities (e.g., acquisition, consumption, and disposal) related to a product or service, while traditional marketing tends to focus on the firm level and acquisition/purchase activity only.

Due to the significance of AIM, it has become an essential tool that is fast becoming part of most businesses to create, disseminate, and apply knowledge. Many reports have been published over recent years about the potential of AI to improve marketing substantially [4][5]. Based on a survey conducted by Accenture [6], 86% of the C-suite executives believed that it is important to scale AI across their businesses, and 76% believed the risk of going out of business if they fail to implement it within the next five years. Based on another survey published in [7], more than 1400 business-to-business (B2B) marketing executives believed that the top sector to embrace AI is the professional services sector. Nevertheless, the use of AIM has been conservative, and most of the applications are still at the experimental stage [8].

This timely paper synthesizes the literature and develops an AIM framework that guides the strategic adoption of AI in marketing for enhancing customer relationship in a systematic manner. This is achieved by bringing together a diverse range of AIM literatures, which are interdisciplinary in nature, to explore and understand what these literatures can tell us about this topic from the foundational perspective, which is an important role of the artificial intelligence and marketing academia. This paper also uses web resources, particularly real-life examples and cases, to support the discussion of mainstream literature. The remainder of this paper is organized as follows. We revisit the key definitions of various types of customer relationships for a unified view of this topic in Section 2 . We synthesize the literature and develop the AIM framework and explain its attributes in Section 3 . We conduct an analysis using collected examples of marketing innovations in the literature to explain how they have been implemented based on the AIM framework developed through a synthesis of the literature to enhance customer relationship in Section 4 . We present agenda for future research in Section 5 . Finally, we conclude the paper. This paper complements a review paper [2] that focuses on bibliometric analysis. In addition, this paper explores this topic from the interdisciplinary perspective, and thus the rigorous technical descriptions of the AI approaches are excluded, such as the application of an AI approach called support vector data description to identify the target list of prospects while reducing the required training time in [9].

2. AIM Framework

The pre-processor component receives and processes big data, stores selected data and information in the memory storage, and passes processed structured data to the main processor. The rest of this section explains the input data and operation of the pre-processor component.

In the big data era, most data, including the marketing data, possesses the 5Vs characteristics. First, the high volume of data is sourced from various platforms, such as social media [10] and Internet of things platforms [11][12], as well as different groups of people, including potential customers and users. Second, the high velocity of data is generated in a real-time manner. Third, the high variety of data is in the forms of text, image, audio, sensing outcomes, etc. Fourth, the high veracity of data requires a high degree of accuracy and reliability, prompting the need for unstructured data to be processed and irrelevant data to be removed. Fifth, the high value of data creates potential social and economic values in improving customer relationship. The big data can be characterized by either structured or unstructured, and media types, as explained in the rest of this section.

Data types. In general, the big data collected by pre-processor has two types. First, the structured data follows a standardized predefined schema, such as social media ratings, customer demographics, and transaction data. Second, the unstructured data does not follow a standardized predefined schema, such as customer experiences shared in blogs and reviews, and customer feedback gathered in comment boxes in online forms, and thus it is interspersed with homonyms, homophones, homographs, as well as dialects, jargons, slangs, and spelling errors. Both structured and unstructured data can be sourced from internal staff and external people, including potential customers, existing customers (e.g., consumer interactions with the brand), and competitors (e.g., competitors' strategies).

Meanwhile, deep learning is a relative new learning paradigm that integrates the multilayer perceptron approach, which consists of a large number of layers of neurons, into supervised and reinforcement learning approaches. Such integration has shown to address the shortcomings of the original learning paradigms [13]. Overall, further investigation can be pursued to explore and exploit the use of the reinforcement learning and deep learning approaches since the need for human effort to categorize data using labels has become a mammoth task with big data.

3. Applications of the AIM Framework

Table 1 analyses how notable real-life examples and cases of marketing innovations have been implemented following the AIM framework developed through a synthesis of the literature, particularly the pre-processor and main processor, in Section 3 , to enhance customer relationship.

Table 1. Examples of the applications of the AIM framework to marketing innovations for improving customer relationship.

Customer Relationship Area	Example of AIM Applications	Mechanisms for Improving Customer Relationship	Pre-Processor	Main Processor
Customer trust	**IBM's Watson health performs medical diagnostics and dispenses medical advice on most types of diseases, including cancer. It monitors and stores a massive amount of protected health information (PHI). Encryption is used to improve customer trust [14].**	**Encrypt PHI in transit and memory storage in compliance with the health insurance portability and accountability act (HIPAA). Multiple levels of encryptions, such as disk, file system, and application, are used.**	**Receive structured data (i.e., age and medical laboratory results) and unstructured data (i.e., radiology images and patient symptoms).**	**Provide a list of possible diseases and their respective confidence levels. Knowledge is stored in cloud.**

Customer Relationship Area	Example of AIM Applications	Mechanisms for Improving Customer Relationship	Pre-Processor	Main Processor
Customer satisfaction	L'Oréal's ModiFace shows real results of virtual makeup with different makeup and hair colour try-ons on personal images in real time for personalized experience, followed by augmented reality shopping. It identifies images on social media and promotes latest trends in makeup [15].	Provide personalized offerings with the right selection of products to match with customer needs.	Receive unstructured data (i.e., face images).	Provide recommendations on makeup and hair colours. Knowledge is stored in cloud.
	Hubspot uses natural language processing [2] to perform automated conversation with human in different channels, such as websites and applications [16]. The conversation provides access to information and performs automated tasks, such as making a reservation in a restaurant, booking appointments, and generating leads [17].	Interact with prospects and customers, and answer questions that they ask. Conversation can also be redirected to a staff whenever necessary.	Receive structured data (i.e., booking information) and unstructured data (i.e., customer questions and requests).	Provide recommendations for requests based on prospects and customers' context, intention, and emotion.
Customer commitment	Schnuck market robots ensure a resilient supply chain [2] by optimising the inventory level according to customer demand and managing stock availability and arrangement on shelves.	Provide accurate real-time inventory information with streamlined ordering and replenishment to match with customer demand [18].	Receive structured data (i.e., real-time sensing outcomes) from sensors.	Provide recommendations for inventory ordering and replenishment.
Customer engagement	Chatbots have been used in firms, such as Sephora [19] and H&M [20], to provide recommendations to customers based on their past transactions and inferred preferences.	Provide personalized customer engagement marketing that creates, communicates, and delivers personalized offerings with the right selection of products, prices, promotions, and places (i.e., website content) to match with customer preferences [3].	Receive structured data (i.e., past transactions and inferred preferences) and unstructured data (i.e., customer requests).	Provide recommendations on products.
	Adobe Sensei searches for the right contents (e.g., advertisements) in different media (e.g., text, image, audio, and video), customises them for the right target segments and individuals, and then presents the contents via the right channels at the right time [17].	Provide personalized advertisements designed based on the prospects' needs and preferences, such as budget and the communication channel type, to nurture and qualify leads [17].	Receive structured data (i.e., budget and communication channel type) and unstructured data (i.e., prospects' needs and preferences).	Provide recommendations on products.
Customer loyalty	Marriott International records and analyses customer activities (e.g., viewing and purchasing an item, and writing a review about the item), and then incentivizes loyal customers [2].	Provide personalized incentives to match with loyal customers' preferences in order to optimize the values and effectiveness of the incentives [2].	Receive structured data (i.e., customer activities).	Provide recommendations on incentives.

We explain an example of innovation, particularly how bridge [21][22][23] can be adopted in the AIM framework. Bridge connects an entity (e.g., a customer, social network user [23], business, or service) to numerous different sub-networks (e.g., customer reviews about a business or service), allowing the entity to be made known to them. An enhanced approach called k -bridge [24] is proposed to relate an entity to overlapping sub-networks, which is useful in AIM.

Various AI and learning approaches have been proposed to enable bridge in various applications [25][26][27][28][29][30], and bridge can be applied to the three main components, namely pre-processor, the main processor, and the memory storage. The peculiarities of k -bridges (i.e., users) have been applied to define crawling strategies to seek for new and updated contents in social networks, which is a significant process in the pre-processor of the AIM framework [22]. Bridges have also been applied to provide recommendations on: (a) businesses and products to prospects; (b) other users whom a user can interact with; (c) and suggestions for text used in writing new reviews [24]. These are significant processes in the main processor of the AIM framework. Other applications include to: (a) understand information diffusion and how users (i.e., customers and prospects) interact in social networks [27]; (b) understand how ratings are dynamically assigned to businesses [28] (e.g., the types of events [29]); (c) analyse the review contents from the sentimental perspective [30]; and explore other related information, such as patents [31][32].

In [24], k -bridge is applied to find the right target segments and individuals in order to increase market share. Using k -bridge, different sub-networks (e.g., businesses and services) are linked to provide diffusion points. The recommended new business is selected based on a metric calculated based on relevant factors, including the number of friends of a bridge (e.g., existing customers) and the time interval in which the bridge performs activities. Using k -bridge helps to recommend new businesses to existing customers based on their current and selected businesses.

4. Agenda for Future Research

Using AI, the learning mechanism maximizes or minimizes an objective function, which captures the rewards (or penalties) for the appropriate (or inappropriate) marketing actions selected under certain environments. Examples of rewards are maximizing customer satisfaction, customer retention, sales and profits, market share, etc. Penalties capture the opposite of rewards, and an example is customer churning. While crafting the objective function based on general goals may lead to an improved overall performance, unfavourable consequences related to bias and discrimination may occur occasionally due to the lack of awareness on inclusive and sensitivity. As an example, in customer engagement, the machine may make gender-biased decisions that promote some products to a certain group of people, causing the rest to miss a promotion opportunity. As another example, in customer engagement, the machine may not choose to promote a product to a certain racial group of people, most of whom have a history of preferring another product. Imagine a machine that shifts its focus to promote products and promotion to profitable customers of a certain group of people with the same gender or race, such action can cause the other groups to become disgruntled and expedite their churning. Further investigation may be pursued to minimize social bias and discrimination to improve customer trust.

“Understanding the reasons behind predictions is, however, quite important in assessing trust, which is fundamental if one plans to take action based on a prediction, or when choosing whether to deploy a new model. Such understanding also provides insights into the model, which can be used to transform an untrustworthy model or prediction into a trustworthy one.”

Customer relationship mainly concerns human interactions and customer behaviours, and thus building and maintaining a positive customer relationship relies on common sense and tacit knowledge. While AI can learn explicit knowledge, which can be described and shared in words (e.g., written down in books, guides, and standard operations), the opposite applies to tacit knowledge. Tacit knowledge are skills and “know-hows” that cannot be easily described and shared in words, such as a firm’s culture and innovation in decision makings, the persuasive tactics in customer engagement, and the knowledge embedded in emotion related to customer satisfaction. Such knowledge is best learned through observation, imitation, and practice (or experience).

Customer, user, and external market knowledge (see Section 3.3) are seen as the new gold for improving customer relationship in the big data era. Since we are still in the early stages of using AI in marketing focusing on weak AI (see Section 3.2.1), there is still a long way to go to unlock the full potential of the knowledge.

Firms can identify the activities related to customer relationship that are suitable for machines and to what degree AI can be used, particularly those that harness the strength of weak AI, including those that require emotion intelligence (see Section 5.1) and tacit knowledge (see Section 5.4). Once the activities related to customer relationship are identified, it is necessary to understand how customer, user, and external market knowledge can be captured and transferred to machines effectively, which can be based on structured or unstructured data in different media types, such as text, image, and audio (see Section 3.1.1). Since such activities are likely to have been performed by human, how AI can impact the human role, whether it improves or degrades customer relationship, staff knowledge, and staff performance, can be investigated. Suitable learning paradigms and AI approaches (see Section 3.2) can be selected to perform the activities related to improving customer relationship. Learned knowledge can be stored in the memory storage (see Section 3.3). Then, investigations can be conducted to understand how the selected AI approach can improve the value creation process. Given the highly dynamic and competitive business environment, the learned knowledge changes and thus are the marketing actions to improve the various aspects of the activities. Overall, improving customer relationship is the fertile ground for AIM, and this open issue has established the motivation for enhancing customer relationship using AI.

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