

Review

Artificial Intelligence Marketing (AIM) for Enhancing Customer Relationships

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Abstract: Based on the literature, we present an artificial intelligence marketing (AIM) framework that enables autonomous machines to receive big data and information, use artificial intelligence (AI) to create knowledge, and then disseminate and apply the knowledge to enhance customer relationships in a knowledge-based environment. To develop the AIM framework, we bring together and curate a wide range of relevant literatures including real-life examples and cases, and then understand how these literatures contribute to the framework in this research topic. We explain the AIM framework from the interdisciplinary perspective, which is an important role of both the artificial intelligence and marketing academia. The AIM framework includes three main components, including the pre-processor, the main processor, and the memory storage. The main processor, which is the key component, uses AI to process structured data processed by pre-processor in order to make real-time decisions and reasonings. The AI approach is characterized by its hypothetical abilities, learning paradigms, and operation modes with human. The strategic use of the developed AIM framework based on the literature to enhance customer relationships, including customer trust, satisfaction, commitment, engagement, and loyalty, is presented. Finally, future potential investigations are presented to drive forward this interdisciplinary research topic.

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

Artificial intelligence (AI) is one of the main disruptive technologies that enables machines to mimic human cognitive and effective functions essential for performing intellectual tasks, such as problem solving and reasoning, in an autonomous manner [1]. Based on past experiences and existing knowledge, machines represent, learn, store, and refine their knowledge progressively in order to make real-time decisions (e.g., selecting marketing actions) and reasonings (e.g., predicting customer satisfaction) [2]. Learning occurs when machines assess the decisions made against correct answers, and in certain cases, against criteria when there is lack of well-defined answers. The learned knowledge enables machines to adapt and respond to the ever-changing business environment, which is unachievable using the traditional approaches that generally use a predefined set of static rules. Over the years, the advent of AI has changed the marketing landscape and channels from the traditional approaches using printed catalogues and telemarketing to the current digital approaches, such as using social networks and chatbots.

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” [3]

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 [4]. Such capability enables AIM to go the extra length to manifest personalization [5] 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 [6,7]. Based on a survey conducted by Accenture [8], 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 [9], 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 [10].

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 [4] 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 [11].

2. Revisiting Customer Relationship

The diversity of the definitions of customer relationship has prompted this section to present the well-established definitions and examples of customer relationship. There are five main types of customer relationships as shown in Table 1. While the definitions are self-explanatory, customer commitment and customer loyalty are carefully explored and explained in [12] due to their seemingly marginal differences. In [12], customer commitment has a larger scope covering "customer emotional feelings and desire to maintain relationship with a brand as a result of deeper intrinsic factors like the brand

meaning and image from customers perspective”, while customer loyalty simply means customers continue to rebuy or repatronize a preferred product or service consistently in the future. Various forms of customer relationships are interrelated, although they are explained separately in Table 1. As an example, improving customer satisfaction helps to improve customer loyalty as satisfied customers tend to rebuy or repatronize a product or service. As another example, improving customer commitment, particularly emotional bonding, helps to create a positive relationship that helps customer engagement to progress well [13].

Table 1. Customer relationship definitions and examples of provision.

Customer Relationship	Definition	Examples of Provision
Customer trust	“... the expectations held by the consumer that the service provider is dependable and can be relied on to deliver on its promises.” [14]	<ul style="list-style-type: none"> • Promote stringent customer data protection. • Create and share video testimonials from customers.
Customer satisfaction	“... consumer’s response in a particular consumption experience to the evaluation of the perceived discrepancy between prior expectations (or some other norm of performance) and the actual performance of the product as perceived after its acquisition.” [15]	<ul style="list-style-type: none"> • Provide personalized customer experience and support. • Increase employee awareness towards customers’ needs.
Customer commitment	“... an enduring attitude or desire for a particular brand or firm.” [16]	<ul style="list-style-type: none"> • Keep a promise to ensure on-time delivery and follow through it. • Provide exclusivity, such as an exclusive access to a channel in television subscriptions offered by broadcasting firms.
Customer engagement	“.. customer engagement behaviors go beyond transactions, and may be specifically defined as a customer’s behavioral manifestations that have a brand or firm focus, beyond purchase, resulting from motivational drivers” [13]	<ul style="list-style-type: none"> • Send a welcome message to customers. • Reward customers after collecting sufficient points.
Customer loyalty	“... a deeply held commitment to rebuy or repatronize a preferred product or service consistently in the future, despite situational influences and marketing efforts having the potential to cause switching behaviour.” [17]	<ul style="list-style-type: none"> • Introduce VIP tiers (or loyalty ladders) such that repeated purchases increase a customer’s tier and rewards. • Introduce referral programs that reward customers for their recommendations.

3. AIM Framework

We synthesize the literature and develop an AIM framework that enables autonomous machines to create, disseminate, and apply knowledge for enhancing customer relationship in a knowledge-based environment. The framework receives and translates big data into information and knowledge [9] and improves a firm’s knowledge potential progressively. The knowledge provides a key source of competitive advantage in enhancing customer relationship. Throughout this section, the literature (or references) is synthesized to contribute to the AIM framework and provides examples of the contributions.

AIM offers four notable advantages that improve customer relationship. First, it increases the efficiency of marketing activities. For instance, AIM automates repetitive tasks, including searching for, collecting, analysing, and processing data, to facilitate problem solving and reasoning in a real-time manner. Second, AIM increases the accuracy of decisions made in problem solving and the predictions made in reasonings based on big data. Third, AIM increases availability since it operates 24/7. Fourth, it reduces the cost of serving customers and improves financial gains.

The AIM framework is shown in Figure 1. There are three main components, including pre-processor, main processor, and memory storage. To understand the framework, we summarize its attributes in Figure 2. The rest of this section explains the framework in a greater detail. We also identify the gaps and open issues of the main components in the framework that require attention in the research domain.

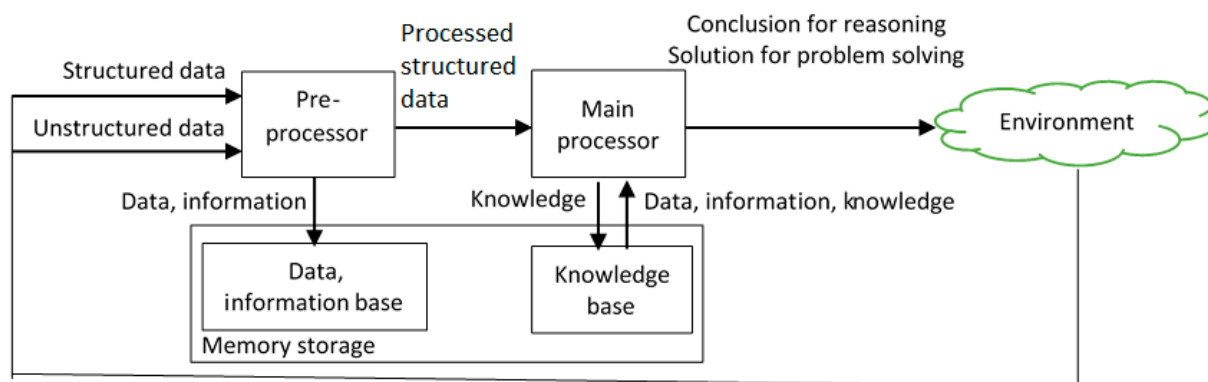


Figure 1. The AIM framework developed through a synthesis of the literature.

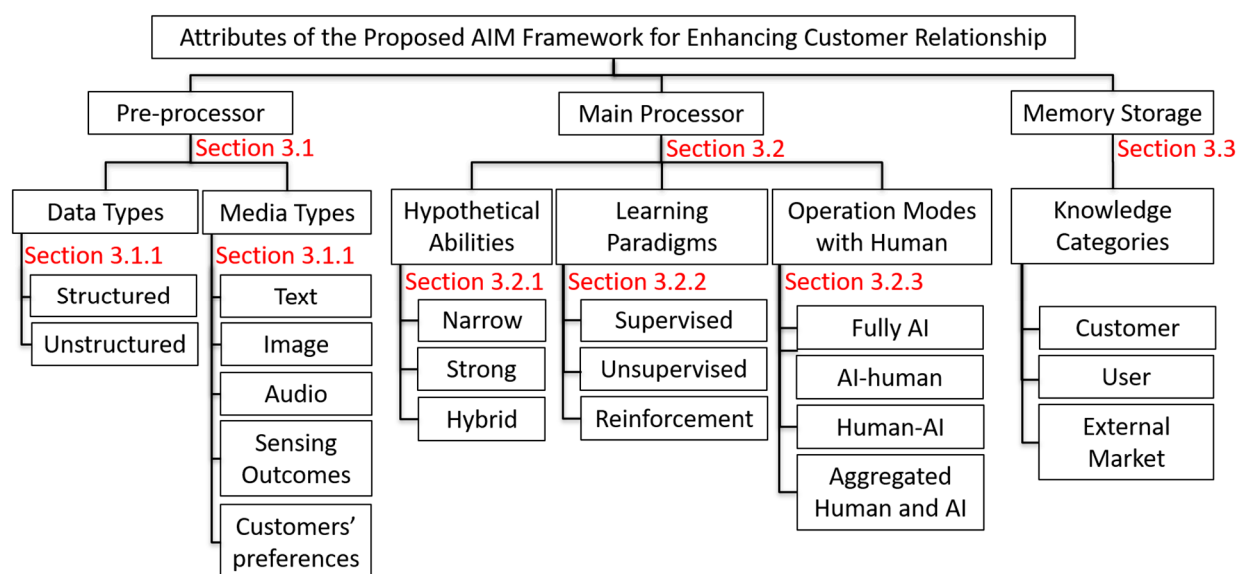


Figure 2. The attributes of the AIM framework for enhancing customer relationship.

3.1. Pre-Processor

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

3.1.1. The Inputs of Pre-Processor

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 [18] and Internet of things platforms [19,20], 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).

Media types of data. While humans perceive their environment through their senses (i.e., eyes, ears, nose, tongue, and skin), machines use input devices and sensors to receive structured and unstructured data of various types of media [10] as seen in real-life examples and cases (see Table 2). Further investigation can be pursued to exploit the use of video as the input medium despite its complexity due to its increasing popularity.

Table 2. Media used by AIM.

Medium	Description	Examples of the Use of Media for AIM
Text	Recognize handwritten or typewritten text, and then provide assistance and recommendations.	<ul style="list-style-type: none"> IBM Watson [21] and Alpine AI [22] provide virtual text assistant.
Image	Recognize images, and then provide assistance or recommendations.	<ul style="list-style-type: none"> KFC recognizes face for payment approval [23]. Shiseido [24] and Estée Lauder [25] recognize face skin conditions and suggest cosmetic products. eBay recognizes images and festivals and recommends products [26]. FashionAI recognizes body images and suggests clothes [27].
Audio	Recognize voice, and then provide assistance or recommendations.	<ul style="list-style-type: none"> Google Assistant provides virtual audio assistance [28]. Amazon Alexa processes voice purchase requests [29].
Sensing outcomes	Gather sensing outcomes using sensors in a real-time manner and use them as guides to provide assistance and recommendations.	<ul style="list-style-type: none"> StretchSense uses sensors to measure customers' figures when ordering custom tailor clothes [30].
Customers' preferences	Gather customers' inputs in a real-time manner and use them as guides to provide assistance and recommendations.	<ul style="list-style-type: none"> Naver, which is a GPS navigation assistant, suggests attractions along a route and similar places to destinations [31]. IBM Watson IoT detects and eliminates unfavourable events (e.g., a lift breakdown) [32]. Intelligentx Brew recommends new recipes [33]. Spotify [34] and Emirates [35] recommend travel destinations. Monteloeder recommends UV products based on smartphone locations and time [36]. iperfumy.pl, kontigo.pl, and ING Bank Śląski recommend advertisements for products within the right price range based on shopping records and smartphone models [10,37].

3.1.2. The Operations of Pre-Processor

The pre-processor component gathers a massive amount of structured and unstructured data related to firm, market, and customer requirements and behaviours, and then transcribes and transforms the vast and complicated data, including human language, into meaningful and insightful semantic representations. Unstructured data is transformed into structured data [38]. Unreliable data, such as fake news from social media and search engines, is removed. Natural language processing (NLP), which can be based on AI, has

been widely used to analyse the syntax, semantics, and pragmatics of sentences based on lexicon and grammar rules.

3.2. Main Processor

The main processor component responds to real-time market conditions and customer requirements, which are crucial to establishing and maintaining long-term and personalized customer relationship [38]. The main functions are to: (a) transform structured data (raw facts) to information (meaningful facts in a formative context) in a value-creating manner; (b) learn and relearn marketing knowledge (e.g., patterns and insights); and (c) make decisions for problem solving and reasoning in response to current and predicted market conditions in a real-time manner [4]. Problem solving identifies the best possible solutions and strategies for different types of problems. Examples of problem solving in customer engagement are to: (a) perform STP (i.e., segmentation, targeting, and positioning); (b) develop a customer engagement strategy based on current and future customer profiles; (c) identify high-quality leads in customer engagement; and (d) follow up orders and purchases. Reasoning executes logic processes based on available structured data to deduce conclusions (e.g., patterns and rules) [38].

3.2.1. Hypothetical Abilities

According to [2], there are three main hypothetical abilities of AI. First, *narrow AI* (or weak AI) performs specific tasks only; thus, it must be modified and/or re-trained to perform other tasks. Despite being inflexible, it performs the specific tasks well, and outperforms human intelligence. Second, *strong AI* (or artificial general intelligence or full AI) performs various types of tasks similar to humans, rather than specific tasks only. This means that strong AI is as flexible as human intelligence that not only learn, but to “learn to learn” [39]. Strong AI is conceptual and has not been achieved yet. Third, *hybrid AI* combines multiple narrow AI approaches to perform more complex specific tasks.

At present, most, if not all, AIM approaches proposed in the literature fall into the narrow AI category [38]. Both strong and hybrid AI approaches can be explored to uncover the full potential of AIM.

3.2.2. Learning Paradigms

In the AI literature, there are three main types of AI learning paradigms that enable a main processor to learn. Some of the AI learning paradigms used in AIM to implement real-life examples and cases are summarized in Table 3.

First, *supervised learning* requires human effort to categorize data using labels, which represent known feature(s), and then train a machine using the labelled data. For instance, customers in the database can be categorized and labelled as high-profit, mixed-bag, and losing. The machine minimizes a loss function, which is based on the difference between the real outputs of the machine and the expected outputs based on the labelled data. This approach has been popularly applied in AIM as shown in Table 3. Second, *unsupervised learning* does not use labels and enables a machine to learn on its own, such as the k-means and hierarchical clustering approaches to cluster similar entities, as well as approaches to simplify high-dimensional data. Nevertheless, unsupervised learning has not been applied to complex problems [1]. Third, *reinforcement learning* enables a machine to learn in a trial-and-error manner while interacting with real-time data [1]. The machine observes real-time data (e.g., a customer’s data and the business environment data), learns, selects marketing actions (e.g., advertising campaigns, launching promotions, and adjusting prices), and receives reward or punishment (e.g., the long-term profitability of a customer). Appropriate actions are rewarded, and inappropriate actions are penalized. Thus, the machine learns the best possible actions given different sets of real-time data as time goes by.

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 [40]. 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.

3.2.3. AIM Operation Modes with Human

AIM involves human and machines, and there are four ways to achieve this [41]. First, fully AI replaces human with machines, such as recommending advertisement in a real-time manner. Second, AI-human enables AI to monitor, gather, and analyse data to provide useful information for human to make decisions, such as making a hiring decision to improve customer relationship. Third, human-AI enables human to monitor and gather data to be provided to AI to make decisions, such as monitoring a human health condition. Fourth, aggregated human and AI enables both human and AI to contribute to different parts of the decision-making process. While the first approach replaces human intelligence with machines, the other three approaches complement human intelligence with superior machine capabilities, particularly high computational and storage capabilities for handling accurate and comprehensive data sets, which helps to provide a higher quality decision-making and reasoning processes.

The operation modes with human participation are useful in their own accord due to the diversity of the marketing problems and decisions. The considerations for choosing an appropriate operation mode are explained in [41]. In the fully AI approach: (a) the problems are well defined and well structured; (b) the problems, which are not new and exceptional, can be solved using prior knowledge; (c) the problems are large; (d) the decisions are generated in a real-time manner; (e) the decisions are measurable; (f) the decisions are not interpretable in which the reasons for the decisions can be unclear and uncertain at times [10]. The rest of the operation modes relax certain criteria in these considerations. For instance, the aggregated human and AI approach is more suitable for solving a new or exceptional problem where prior knowledge is unavailable.

At present, most, if not all, AIM approaches proposed in the literature fall into the fully AI and human-AI categories. Both AI-human and the aggregated human and AI approaches can be explored to uncover the full potential of AIM.

3.2.4. The Outputs of Main Processor

The main processor produces two main types of outputs: (a) conclusion for reasoning, such as the patterns of customer churning, the needs of the customers in the past and in the future; (b) solutions to problem solving, such as optimizing search engines, mapping content to user profiles, generating displays for advertisement, and generating human-like responses interspersed with dialects, jargons, and slangs. The main processor executes marketing actions and interacts with potential and existing customers who generate structured or unstructured data in the environment. Feedback in the form of structured and unstructured data is fed back to pre-processor, and thus AIM is a continuous cycle that improves the accuracy of its decisions for problem solving and reasoning as time goes by.

3.3. Memory Storage

The memory storage component of a machine organizes and stores data, information, and knowledge, which may be shared with other decision-making machines [42]. This enables AIM to monitor the changing customer trends, such as from going to cinema to streaming videos online during and post COVID-19 pandemic. This means that marketing tools can act based upon real-time and dynamic data, information, and knowledge, rather than static categories of customer needs. Such a capability is essential in a dynamic business environment with varying degrees of customer heterogeneity, including customer preferences, demographics, spending potentials, transaction frequencies, etc.

Knowledge can be streamlined into three categories [43]. First, customer knowledge, which is important to improve customer relationship, includes demographic features, web

browsing, and purchasing patterns. An important user knowledge are the purchasing decisions, such as what, how, and why a purchase decision has been made, as well as the antecedents and consequences of the purchase [44]. Second, user knowledge, which is important to develop new products for the future market, includes psychographic characteristics (e.g., needs, attitudes, and insights towards the products) in user experiences, as well as future needs and wants, of the products. Third, external market knowledge, which is important to strengthen one own's marketing strategy, includes competitors and their marketing strategies and product launches, and fake news, which can damage a firm's reputation. Research findings in [43] show that external market knowledge has a significantly higher impact compared to customer and user knowledge. The knowledge is stored in the knowledge base of the memory storage as shown in Figure 1.

Table 3. Learning paradigms and their types of AI approaches.

Learning Paradigm	AI Approaches	Description	Examples of the Use of Media for AIM
Supervised learning	Multilayer perceptron (MLP) (or artificial neural network (ANN)) [40]	A feedforward neural network that contains multiple layers of neurons (or computational units), and each neuron is connected to neurons in the subsequent layer.	<ul style="list-style-type: none"> • Predict customer churning [45] • Evaluate customer loyalty [46]
	Convolutional neural network (CNN) [47]	A feedforward neural network, which is based on the deep learning approach, that contains at least one convolutional layer to learn different aspects (or dimensions) of data or image, and then combine these aspects for identification.	<ul style="list-style-type: none"> • Predict patterns of customer churning (e.g., the sequence of incident, customer complaint, and failure to solve problems [1])
Supervised or unsupervised learning	Recurrent neural network [47], including long short-term memory (LSTM)	A neural network that uses a feedback loop to feed outputs back to the input. The input characteristics (e.g., the input length) can be variable, rather than fixed in MLP and CNN.	<ul style="list-style-type: none"> • Predict customer behaviours [48,49]

4. Applications of the AIM Framework

Table 4 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 4. 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 [50].	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 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 [51].	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 [4] to perform automated conversation with human in different channels, such as websites and applications [52]. The conversation provides access to information and performs automated tasks, such as making a reservation in a restaurant, booking appointments, and generating leads [38].	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 [4] 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 [53].	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 [54] and H&M [55], 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 [5].	Receive structured data (i.e., past transactions and inferred preferences) and unstructured data (i.e., customer requests).	Provide recommendations on products.

Table 4. Cont.

Customer Relationship Area	Example of AIM Applications	Mechanisms for Improving Customer Relationship	Pre-Processor	Main Processor
	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 [38].	Provide personalized advertisements designed based on the prospects' needs and preferences, such as budget and the communication channel type, to nurture and qualify leads [38].	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 [4].	Provide personalized incentives to match with loyal customers' preferences in order to optimize the values and effectiveness of the incentives [4].	Receive structured data (i.e., customer activities).	Provide recommendations on incentives.

We explain an example of innovation, particularly how bridge [56–58] can be adopted in the AIM framework. Bridge connects an entity (e.g., a customer, social network user [58], 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 [59] 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 [60–65], 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 [57]. 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 [59]. 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 [62]; (b) understand how ratings are dynamically assigned to businesses [63] (e.g., the types of events [64]); (c) analyse the review contents from the sentimental perspective [65]; and explore other related information, such as patents [66,67].

In [59], *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.

5. Agenda for Future Research

This section presents research gaps in this interdisciplinary research topic for future investigations. The research gaps aim to improve the main processor, which is the main component, of the AIM framework. Towards the end of this section, we present a summary of research gaps and their relevance to the AIM framework.

5.1. Applying Emotion Attitude Intelligence to Further Improve Customer Relationship

“There is no separation of mind and emotions; emotions, thinking, and learning are all linked.” —Eric Jensen

Emotional intelligence enables machines to recognize and quantify human emotion and attitude, which is important in handling customer relationship. Different approaches are needed when different media types are used. Examples are to recognize and quantify: (a) the level of dissatisfaction based on a text complaint written in an online review; (b) the level of dissatisfaction in an audio call from an angry customer; and (c) the happy facial expressions seen in an image and a video [68]. Naturally, a machine does not possess emotional intelligence. Hence, a machine that categorizes an emotion accurately does not feel the emotion itself. Similarly, a machine that prevents an accident does not understand the importance of life. This opens another area of learning that AI can explore and exploit, whereby the right emotion is related to the right sets of actions in order to improve the common sense of machines. Ultimately, emotional intelligence helps machines to understand customer emotion in order to enhance customer relationship in an unobtrusive manner, whereby customers and users are unaware to have interacted with machines [69]. Emotion intelligence is important to: (a) encourage customers to interact with machines and humans in the same way [70,71]; (b) optimize media content in an advertisement in order to identify the right leads and improve their satisfaction; and (c) determine when to stop displaying an advertisement without annoying customers [38]. Further investigation can be pursued to introduce emotion intelligence into the AIM framework.

5.2. Defining the Right Objective Functions to Prevent Bias and Discrimination while Improving Customer Relationship

“Much has been written about AI’s potential to reflect both the best and the worst of humanity. For example, we have seen AI providing conversation and comfort to the lonely; we have also seen AI engaging in racial discrimination.” —Andrew Ng, Google Brain

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.

5.3. Improving the Explainability and Interpretability of AI to Improve Sensibility while Enhancing Customer Relationship

“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.” —Ribeiro, Singh, and Guestrin [72]

Understanding the reasons behind the AIM output is important to ensure only reliable and appropriate actions are suggested for intellectual tasks, such as classification,

prediction, and action recommendation. There are three main concerns: (a) whether the output is sensible and appropriate; (b) whether the input or the data source is reliable; and (c) how the inputs are related to the outputs.

Theoretically, imposing rules to ensure that the output falls within an acceptable range can address concern (a), although this may defeat the purpose of providing flexibility in some applications, such as the graphical design of an advertisement. Another point is that, theoretically, ensuring that the input data is reliable can address concern (b); however, with the massive amount of big data, this has become a wearisome task that requires automation, which may cause another issue. Unfortunately, there has not been any concrete solutions proposed to address concern (c) to understand how AI generates outputs based on inputs. Understanding how AI works is tantamount to seeking an explanation on how our brain works, and we do not naturally ask how the mechanics of the brain function and arrive to a decision. Nevertheless, solving concerns (a) and (b) may reduce the need for (c), and this approach can be used to improve the explainability and interpretability of AI if necessary.

As an example, the demand for bottled water surges during water rationing, causing AIM to increase its selling price in response to the sharp decline of supply. Such action is not sensible as the respective company is seen to garner profit at the wrong timing, causing concern (a). This can be addressed by ensuring that the output, which is the selling price, falls within an acceptable range during water rationing. While understanding the explainability and interpretability of AI remains an open issue in the AI domain itself, further investigation could be pursued to investigate the effects of the lack of such capabilities and improve the trustworthiness of AIM for enhancing customer relationship.

5.4. Increasing the AI Capability to Learn Tacit Knowledge

“The thing that’s going to make artificial intelligence so powerful is its ability to learn, and the way AI learns is to look at human culture.” —Dan Brown in [73]

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).

The key issue is, therefore, how best to represent the tacit knowledge that cannot be transferred in language. It is unfortunate that the vast amount of knowledge in improving customer relationship has the nature of being tacit. Further investigation could be pursued to enable AIM to learn tacit knowledge for enhancing customer relationship. First, what types of data and information, which is not necessarily written down, should be gathered. This helps to transfer tacit knowledge from human to machines. Second, how to represent tacit data, information, and knowledge in AIM. Third, how to transfer the learned tacit knowledge constructs back to human for verification. This helps to improve customer trust.

5.5. Using AI to Gather and Harness Customer, User, and External Market Knowledge

“Why are bots/AI so relevant for digital marketing? For anticipatory intelligence—prompting customer actions to deliver outstanding customer experiences, and personalisation at scale—intimate but automated.” —Ashley Freidlein, Econsultancy

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.

5.6. Summary of Research Gaps and Their Relevance to the AIM Framework

Table 5 summarizes the research gaps and shows their contributions to the main processor component of the AIM framework. The description is based on the attributes of the AIM framework presented in Figure 2.

Table 5. Research gaps and their contributions to the AIM framework.

Research Gap	Contributions to the AIM Framework
Applying emotion attitude intelligence to further improve customer relationship	Enables learning paradigms (i.e., supervised, unsupervised, and reinforcement) to perform three main operation modes with human (i.e., fully AI, human-AI, and aggregated human and AI) such that the main processor can recognize and quantify human emotions and attitudes (e.g., the level of dissatisfaction and the level of happiness based on online reviews, images, and videos) in activities for improving customer relationship (e.g., customer engagement).
Defining the right objective functions to prevent bias and discrimination while improving customer relationship	Enables learning paradigms to perform three main operation modes with human (i.e., fully AI, human-AI, and aggregated human and AI) such that the main processor can select the right marketing actions without bias and discrimination under certain environments while carrying out activities for improving customer relationship (e.g., customer satisfaction).
Improving the explainability and interpretability of AI to improve sensibility while enhancing customer relationship	Enables learning paradigms to perform all main operation modes with human (i.e., fully AI, human-AI, AI-human, and aggregated human and AI) such that the main processor can: (a) ensure that the output is sensible and appropriate; (b) ensure that the input data source is reliable; and (c) understand how the inputs are related to the outputs, which are important for improving customer relationship (e.g., customer trust).
Increasing the AI capability to learn tacit knowledge	Enables learning paradigms to perform all main operation modes with human such that the main processor can learn, represent, and transfer tacit knowledge to human for improving customer engagement.
Using AI to gather and harness customer, user, and external market knowledge	Enables learning paradigms to perform all main operation modes with human such that the pre-processor can capture customer, user, and external market knowledge and transfer them to machines effectively in order to cater for highly dynamic customer relationship.

6. Conclusions

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. The strategic framework has three main components, namely pre-processor, main processor, and memory storage, and it is developed based on the curation of a wide range of relevant literatures. The main processor can be characterized by its hypothetical abilities, learning paradigms, and its operation modes with human. Despite the comprehensiveness of the proposed AIM framework, there are numerous research opportunities, including: (a) learning emotion or attitude; (b) eliminating bias and discrimination; (c) improving explainability and interpretability; (d) learning tacit knowledge; and (e) exploring various ways to gather and harness customer, user, and external market knowledge.

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References

- De Bruyn, A.; Viswanathan, V.; Beh, Y.S.; Brock, J.K.-U.; von Wangenheim, F. Artificial Intelligence and Marketing: Pitfalls and Opportunities. *J. Interact. Mark.* **2020**, *51*, 91–105. [CrossRef]
- Wirth, N. Hello marketing, what can artificial intelligence help you with? *Int. J. Mark. Res.* **2018**, *60*, 435–438. [CrossRef]
- Kotler, P.; Keller, K.L.B. *Marketing Management*, 15th ed.; Pearson: Essex, UK, 2016; pp. 58–59.
- Verma, S.; Sharma, R.; Deb, S.; Maitra, D. Artificial intelligence in marketing: Systematic review and future research direction. *Int. J. Inf. Manag. Data Insights* **2021**, *1*, 100002. [CrossRef]
- Kumar, V.; Rajan, B.; Venkatesan, R.; Lecinski, J. Understanding the Role of Artificial Intelligence in Personalized Engagement Marketing. *Calif. Manag. Rev.* **2019**, *61*, 135–155. [CrossRef]
- Davenport, T.; Guha, A.; Grewal, D.; Bressgott, T. How artificial intelligence will change the future of marketing. *J. Acad. Mark. Sci.* **2019**, *48*, 24–42. [CrossRef]
- Rust, R.T. The future of marketing. *Int. J. Res. Mark.* **2020**, *37*, 15–26. [CrossRef]
- AI: Built to Scale. Available online: <http://www.accenture.com/gb-en/insights/artificial-intelligence/ai-investments> (accessed on 22 June 2021).
- Professional Services Firms See Huge Potential in Machine Learning. Available online: <https://www.technologyreview.com/2018/11/02/139216/professional-services-firms-see-huge-potential-in-machine-learning/> (accessed on 24 June 2021).
- Jarek, K.; Mazurek, G. Marketing and Artificial Intelligence. *Central Eur. Bus. Rev.* **2019**, *8*, 46–55. [CrossRef]
- Rekha, A.G.; Abdulla, M.S.; Asharaf, S. Artificial Intelligence Marketing: An application of a novel Lightly Trained Support Vector Data Description. *J. Inf. Optim. Sci.* **2016**, *37*, 681–691. [CrossRef]
- Ogba, I.-E.; Tan, Z. Exploring the impact of brand image on customer loyalty and commitment in China. *J. Technol. Manag. China* **2009**, *4*, 132–144. [CrossRef]
- Van Doorn, J.; Lemon, K.N.; Mittal, V.; Nass, S.; Pick, D.; Pirner, P.; Verhoef, P. Customer Engagement Behavior: Theoretical Foundations and Research Directions. *J. Serv. Res.* **2010**, *13*, 253–266. [CrossRef]
- Sirdeshmukh, D.; Singh, J.; Sabol, B. Consumer Trust, Value, and Loyalty in Relational Exchanges. *J. Mark.* **2002**, *66*, 15–37. [CrossRef]
- Day, R.L. Modeling choices among alternative responses to dissatisfaction. In *NA—Advances in Consumer Research*; Kinnear, T.C., Ed.; Association for Consumer Research: Provo, UT, USA, 1984; Volume 11, pp. 496–499.
- Moorman, C.; Zaltman, G.; Deshpande, R. Relationships between providers and users of market research: The dynamics of trust within and between organizations. *J. Mark. Res.* **1992**, *29*, 314–328. [CrossRef]

17. Oliver, R.L. *Satisfaction: A Behavioral Perspective on the Consumer: A Behavioral Perspective on the Consumer*, 2nd ed.; Taylor & Francis Group: New York, NY, USA, 2010.
18. Kietzmann, J.; Hermkens, K.; McCarthy, I.P.; Silvestre, B.S. Social media? Get serious! Understanding the functional building blocks of social media. *Bus. Horiz.* **2011**, *54*, 241–251. [CrossRef]
19. Osmonbekov, T.; Johnston, W.J. Adoption of the Internet of things technologies in business procurement: Impact on organizational buying behaviour. *J. Bus. Ind. Mark.* **2018**, *33*, 781–791. [CrossRef]
20. Turunen, T.; Eloranta, V.; Hakanen, E. Contemporary perspectives on the strategic role of information in internet of things-driven industrial services. *J. Bus. Ind. Mark.* **2018**, *33*, 837–845. [CrossRef]
21. IBM Watson is AI for Business. Available online: <https://www.ibm.com/watson> (accessed on 24 June 2021).
22. Thanking All Involved in the Alpine. AI Journey. Available online: <https://marchick.medium.com/thanking-all-involved-in-the-alpine-ai-journey-793190a9165c> (accessed on 24 June 2021).
23. KFC Launches First AI-Enabled Outlet in Beijing. Available online: <https://retail.economictimes.indiatimes.com/news/food-entertainment/food-services/kfc-launches-first-ai-enabled-outlet-in-beijing/56177544> (accessed on 24 June 2021).
24. Shiseido Launches Internet of Things Skincare System. Available online: <https://fortune.com/2019/07/02/shiseido-optune-internet-of-things-ai-and-ar-skincare-system/> (accessed on 24 June 2021).
25. A.I. in the Beauty Industry: How the Pandemic Finally Made Consumers Care About It. Available online: <https://fortune.com/2021/01/11/ai-artificial-intelligence-personalized-beauty-cosmetics-brainstorm-reinvent/> (accessed on 24 June 2021).
26. The Amazing Ways eBay Is Using Artificial Intelligence to Boost Business Success. Available online: <https://www.forbes.com/sites/bernardmarr/2019/04/26/the-amazing-ways-ebay-is-using-artificial-intelligence-to-boost-business-success/?sh=71f19fcc2c2e> (accessed on 24 June 2021).
27. FashionAI: Revamping the Fashion and E-Commerce Industry Through Artificial Intelligence. Available online: https://www.alibabacloud.com/blog/fashionai-revamping-the-fashion-and-e-commerce-industry-through-artificial-intelligence_595413 (accessed on 24 June 2021).
28. Artificial Intelligence Powered Digital Assistants. Available online: <https://medium.com/voice-tech-podcast/artificial-intelligence-powered-digital-assistants-1e0bdf108641> (accessed on 24 June 2021).
29. Are Alexa and Siri Considered AI? Available online: <https://bernardmarr.com/default.asp?contentID=1830> (accessed on 24 June 2021).
30. Wearable Tech Company StretchSense Makes a Hollywood Comeback. Available online: <https://www.wearable-technologies.com/2020/11/wearable-tech-company-stretchsense-makes-a-hollywood-comeback/> (accessed on 24 June 2021).
31. Naver to Test AI-Based Product Suggestion Service for Personalized Online Shopping Experience. Available online: <https://www.ajudaily.com/view/20201223075926232> (accessed on 24 June 2021).
32. The Evolution of the Watson IoT Platform: Three Key Things You Should Know. Available online: <https://www.ibm.com/blogs/internet-of-things/iot-the-watson-iot-platform-three-key-things-you-should-know/> (accessed on 24 June 2021).
33. How Artificial Intelligence Is Used to Make Beer. Available online: <https://www.forbes.com/sites/bernardmarr/2019/02/01/how-artificial-intelligence-is-used-to-make-beer/?sh=d3cd71670cf4> (accessed on 24 June 2021).
34. The Amazing Ways Spotify Uses Big Data, AI and Machine Learning to Drive Business Success. Available online: <https://bernardmarr.com/default.asp?contentID=1201> (accessed on 24 June 2021).
35. Developing & Implementing Artificial Intelligence & Machine Learning for the Benefit of Business and Society. Available online: <http://eait.com/> (accessed on 24 June 2021).
36. Monteloeder Digital Nutraceutical for You: A New Strategy Is Possible. Available online: <https://www.monteloeder.com/monteloeder-digital-nutraceutical-for-you-a-new-strategy-is-possible/> (accessed on 24 June 2021).
37. AI Works Behind the Scenes to Truly Personalize Your Banking Experience. Available online: <https://impactcee.com/tag/ing-bank-slaski/> (accessed on 24 June 2021).
38. Paschen, J.; Kietzmann, J.; Kietzmann, T.C. Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. *J. Bus. Ind. Mark.* **2019**, *34*, 1410–1419. [CrossRef]
39. Mead, W.R.; Kurzweil, R. The Singularity Is Near: When Humans Transcend Biology. *Foreign Aff.* **2006**, *85*, 160. [CrossRef]
40. Rasheed, F.; Yau, K.-L.A.; Noor, R.M.; Wu, C.; Low, Y.-C. Deep Reinforcement Learning for Traffic Signal Control: A Review. *IEEE Access* **2020**, *8*, 208016–208044. [CrossRef]
41. Stone, M.; Aravopoulou, E.; Ekinci, Y.; Evans, G.; Hobbs, M.; Labib, A.; Laughlin, P.; Machtynger, J.; Machtynger, L. Artificial intelligence (AI) in strategic marketing decision-making: A research agenda. *Bottom Line* **2020**, *33*, 183–200. [CrossRef]
42. Abbate, T.; Codini, A.P.; Aquilani, B. Knowledge co-creation in Open Innovation Digital Platforms: Processes, Tools and Services. *J. Bus. Ind. Mark.* **2019**, *34*, 1434–1447. [CrossRef]
43. Bag, S.; Gupta, S.; Kumar, A.; Sivarajah, U. An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision making for improving firm performance. *Ind. Mark. Manag.* **2020**, *92*, 178–189. [CrossRef]
44. Abrell, T.; Pihlajamaa, M.; Kanto, L.; Brocke, J.V.; Uebernickel, F. The role of users and customers in digital innovation: Insights from B2B manufacturing firms. *Inf. Manag.* **2016**, *53*, 324–335. [CrossRef]
45. Ismail, M.; Awang, M.; Rahman, M.; Makhtar, M. A multi-layer perceptron approach for customer churn prediction. *Int. J. Multimed. Ubiquitous Eng.* **2015**, *10*, 213–222. [CrossRef]

46. Ansari, A.; Riasi, A. Modelling and evaluating customer loyalty using neural networks: Evidence from startup insurance companies. *Futur. Bus. J.* **2016**, *2*, 15–30. [CrossRef]
47. Khan, S.; Rahmani, H.; Shah, S.A.A.; Bennamoun, M. A Guide to Convolutional Neural Networks for Computer Vision. *Synth. Lect. Comput. Vis.* **2018**, *8*, 1–207. [CrossRef]
48. Valentin, J.; Reutterer, T. From RFM to LSTM: Predicting customer future with autoregressive neural networks. In Proceedings of the INFORMS Marketing Science Conference, Rome, Italy, 20–22 June 2019.
49. Sarkar, M.; De Bruyn, A. Predicting customer behaviour with LSTM neural networks. In Proceedings of the INFORMS Marketing Science Conference, Rome, Italy, 20–22 June 2019.
50. Dean, D.J.; Ranchal, R.; Gu, Y.; Sailer, A.; Khan, S.; Beaty, K.; Bakthavachalam, S.; Yu, Y.; Ruan, Y.; Bastide, P. Engineering scalable, secure, multi-tenant cloud for healthcare data. In Proceedings of the IEEE 13th World Congress on Services, Honolulu, HI, USA, 25–30 June 2017.
51. Aarabi, P.; Manashirov, B.; Phung, E.; Lee, K.M. Precise Skin-Tone and Under-Tone Estimation by Large Photo Set Information Fusion. In Proceedings of the 2015 IEEE International Symposium on Multimedia (ISM), Miami, FL, USA, 14–16 December 2015; pp. 507–512. [CrossRef]
52. Arsenijevic, U.; Jovic, M. Artificial intelligence marketing: Chatbots. In Proceedings of the International Conference on Artificial Intelligence: Applications and Innovations, Belgrade, Serbia, 30 September–4 October 2019.
53. Schnuck Markets Rolls Out Shelf-Scanning Robots to Over Half of Store Base. Available online: <https://www.supermarketnews.com/technology/schnuck-markets-rolls-out-shelf-scanning-robots-over-half-store-base> (accessed on 24 June 2021).
54. How Sephora Used Chatbots to Compliment In-Store Service. Available online: <https://www.indigo9digital.com/blog/learn-how-sephora-is-using-chatbots-to-create-a-better-customer-experience> (accessed on 24 June 2021).
55. Chatbot Use Cases that Actually Work. Available online: <https://emerj.com/ai-sector-overviews/7-chatbot-use-cases-that-actually-work/> (accessed on 24 June 2021).
56. Buccafurri, F.; Foti, V.D.; Lax, G.; Nocera, A.; Ursino, D. Bridge analysis in a Social Internetworking Scenario. *Inf. Sci.* **2013**, *224*, 1–18. [CrossRef]
57. Buccafurri, F.; Lax, G.; Nocera, A.; Ursino, D. Moving from social networks to social internetworking scenarios: The crawling perspective. *Inf. Sci.* **2014**, *256*, 126–137. [CrossRef]
58. Buccafurri, F.; Lax, G.; Nicolazzo, S.; Nocera, A. Comparing Twitter and Facebook user behavior: Privacy and other aspects. *Comput. Hum. Behav.* **2015**, *52*, 87–95. [CrossRef]
59. Corradini, E.; Nocera, A.; Ursino, D.; Virgili, L. Defining and detecting k-bridges in a social network: The Yelp case, and more. *Knowl.-Based Syst.* **2020**, *195*, 105721. [CrossRef]
60. Wang, N.; Wang, H.; Jia, Y.; Yin, Y. Explainable recommendation via multitask learning in opinionated text data. In Proceedings of the International ACM SIGIR Conference on Research & Development in Information Retrieval, Ann Arbor, MI, USA, 8–12 July 2019.
61. Chen, X.; Qin, Z.; Zhang, Y.; Xu, T. Learning to rank features for recommendation over multiple categories. In Proceedings of the International ACM SIGIR Conference on Research & Development in Information Retrieval, Pisa, Italy, 17–21 July 2016.
62. Xuan, Q.; Shu, X.; Ruan, Z.; Wang, J.; Fu, C.; Chen, G. A Self-Learning Information Diffusion Model for Smart Social Networks. *IEEE Trans. Netw. Sci. Eng.* **2019**, *7*, 1466–1480. [CrossRef]
63. Singh, R.; Woo, J.; Khan, N.; Kim, J.; Lee, H.J.; Rahman, H.A.; Park, J.; Suh, J.; Eom, M.; Gudigantala, N. Applications of machine learning models on Yelp data. *Asia Pac. J. Inf. Syst.* **2019**, *29*, 117–143. [CrossRef]
64. Gui, L.; Zhou, Y.; Xu, R.; He, Y.; Lu, Q. Learning representations from heterogeneous network for sentiment classification of product reviews. *Knowl.-Based Syst.* **2017**, *124*, 34–45. [CrossRef]
65. Angelidis, S.; Lapata, M. Multiple Instance Learning Networks for Fine-Grained Sentiment Analysis. *Trans. Assoc. Comput. Linguist.* **2018**, *6*, 17–31. [CrossRef]
66. Ferrara, M.; Fosso, D.; Lanatà, D.; Mavilia, R.; Ursino, D. A social network analysis based approach to extracting knowledge patterns about innovation geography from patent databases. *Int. J. Data Min. Model. Manag.* **2018**, *10*, 23–71. [CrossRef]
67. Donato, C.; Giudice, P.L.; Marretta, R.; Ursino, D.; Virgili, L. A well-tailored centrality measure for evaluating patents and their citations. *J. Doc.* **2019**, *75*, 750–772. [CrossRef]
68. Vo, A.-D.; Nguyen, Q.-P.; Ock, C.-Y. Opinion–Aspect Relations in Cognizing Customer Feelings via Reviews. *IEEE Access* **2018**, *6*, 5415–5426. [CrossRef]
69. What Does the Future of Customer Experience Look Like? Available online: <https://www.ama.org/publications/MarketingNews/Pages/what-does-future-customer-experience-look-like.aspx> (accessed on 24 June 2021).
70. Longoni, C.; Bonezzi, A.; Morewedge, C.K. Resistance to Medical Artificial Intelligence. *J. Consum. Res.* **2019**, *46*, 629–650. [CrossRef]
71. Luo, X.; Tong, S.; Fang, Z.; Qu, Z. Machines versus humans: The impact of AI chatbot disclosure on customer purchases. *Mark. Sci.* **2019**, *38*, 913–1084.

-
72. Ribeiro, M.T.; Singh, S.; Guestrin, C. Why should I trust you? Explaining the predictions of any classifier. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, 13–17 August 2016.
 73. Dan Brown on God and Artificial Intelligence in His New Thriller. Available online: <https://www.cbsnews.com/news/dan-brown-on-god-and-artificial-intelligence-in-his-new-thriller-origin/> (accessed on 24 June 2021).