Sustainable Energy Technologies and Assessments 52 (2022) 102103

Contents lists available at ScienceDirect

Sustainable Energy Technologies and Assessments

journal homepage: www.elsevier.com/locate/seta

AI-driven customer relationship management for sustainable enterprise performance

Fangyuan Li [a,b,*], Guanghua Xu [a]

[a] School of Economics and Management, Nanjing University of Science and Technology, Nanjing 210094, China
[b] State Radio Monitoring Center, Beijing 100037, China

ARTICLE INFO

Keywords:
Customer relationship management
Sustainable enterprise
Artificial intelligence
Customer experience

ABSTRACT

Today, Artificial Intelligence (AI) is poised to take on Industry 4.0. Machines have conquered the human interface in complex board games like chess and Chinese games. AIcan now writes poetry, make predictions about decisions, interact with humans in real-time, analyze trillions of data points, and offer solutions in milliseconds. Customer Relationship Management (CRM) is one sector benefiting the most from AI. AI-driven customer relationship management (AI-CRM) technology is proposed in this article. Scholars developed a research method to evaluate product quality, performance, and commitment to AI-enabled technologies. The proposed model is designed with system-level architecture, process-level architecture, and mathematical models to correlate the input and output. A dataset was utilized to obtain primary data acquired by investigators using a survey technique. Data assessment revealed that customers are aware of AI-enabled technologies, that the technique under investigation is successful, and that customers are loyal to them.

Introduction to customer relationship management

Small and medium-sized companies (SMEs) reap the benefits of customer relationship management (CRM) in respect of both consumer knowledge maintenance (CKM) and creativity [1]. Because of this convergence of motivations and advantages, CRM is a vital component for business transformation, pushing SME initiatives toward economic, financial, and environmental sustainability [2]. Small and medium-sized businesses hold over 99 percent of all Chinese companies and two-thirds of private-sector jobs [3]. Caused by the social and economic importance of this industry, the effect of CRM on SMEs is of particular concern.

The administration of consumer research and technology are two of the most important factors in a firm's existence, expansion, and development plans. They improve company efficiency and productivity and provide long-term competitive advantages [4,5]. According to the World Economic Forum, Wissen is the most significant economic resource and even a core component of sustainable competitor benefit [6]. It has been argued that knowledge is necessary for both innovation and competition. According to the experts, information and innovation are intertwined [7,8].

In this context, functioning Consumer Organizational Learning Management (COLM) through innovation activities demonstrates an effective path for information sharing [9]. Academics indeed see consumer cooperation as a contemporary anchor for Consumer Information Management (CIM) and organizational performance and as a system that allows sustainable companies to teach their consumers how to satisfy their requirements and enhance performance [10]. As both a management weapon and a successful business, CRM aimed to address this call to consolidate and integrate consumer cooperation and customer relations [11].

During the 1970s, CRM developed a new tool for corporations to manage and optimize their sales operations [12]. It is heavily used for marketing and advertising and more efficient customer engagement and organizational learning. Understanding organizational culture has become the most prominent organizational Knowledge Management (KM) [13]. According to academics, the best potential knowledge of a company's consumers is sought by integrating procedures, human resources, and technologies.

On the other hand, CRM is the most current integrational technique accessible for relationship management if it concentrates on client retention and customer engagement [14,15]. Collaborative and experimental innovation is essential to a firm's survival and market positioning, notwithstanding the organizational conflicts that emerge from both tendencies [16]. As the heart of modern and dynamic enterprises,

* Corresponding author at: School of Economics and Management, Nanjing University of Science and Technology, Nanjing 210094, China.
E-mail address: lifangyuan_2021@126.com (F. Li).

https://doi.org/10.1016/j.seta.2022.102103
Received 25 December 2021; Received in revised form 29 January 2022; Accepted 17 February 2022
Available online 1 March 2022

sustainable organizational models are based on a mix of present exploitation and future discovery [17]. Positioning your brand or product in the minds of your customers is an important part of any marketing strategy. Promotion, pricing, location, and product are all part of the four Ps. Your positioning plan should be detailed when defining the Ps to be as effective as possible. Resource-Based view holds that a company's ability to build different skills helps it adapt to a shifting competitive landscape and thus increases its chances of survival in the long run.

So the purpose of this research is to show CRM as a technical solution that can assist firms in maximizing their current economic development and investigate and develop in all areas that contribute to sustainable business and market progress. As a result of predicting, objective knowledge of the nature and law of events is gained.

By assessing many factors that influence the sustainable industry and rational models, sales trends, production and consumption changes, and future growth laws are predicted to arrive at a scientific assessment of the state of sales. A time series can estimate and illustrate the trend of overall sales and selling amount for a certain product in the future. The contributions of this paper are as follows:

- To predict the market share prediction, sales goal planning, product pricing planning, etc.
- This study analyses commodities' market income forecast and error assessment using fuzzy logic and artificial intelligence techniques.
- It anticipates the future sales volume using neural network architecture, understands the market's trajectory, and maximizes profits for the clients by using this model to estimate upcoming sales volume.

The rest of the paper is as follows: Section 2 illustrates the background to customer relationship management. The proposed AI-driven customer relationship management (AI-CRM) technology is designed and implemented in section 3. The software analysis and performance evaluation are done in section 4. Section 5 deals with the conclusion and future scope of the proposed model.

Background to the customer relationship management

The nation has been amid a period of rapid technological advancement. Electronic commerce took the next step of fast expansion and intense development [17]. Consumer demand was stimulated, old industries were upgraded, and current financial services developed [18]. Mobile smart connectors were popular, and internet infrastructure was constantly improving [19,20]. It paired with the e-commerce system's ability to provide quick payment methods, insurance, financing, microloans, or other service providers, people's internet shopping prices have skyrocketed, resulting in the rapid growth of online department stores [21,22]. While obtaining more accessible goods product offerings and a larger market atmosphere, businesspeople faced significant obstacles. Predicting price trends and determining how high or low prices will rise or fall is done by charting prices (typically futures). When it comes to analyzing commodities markets, both fundamental and technical analyses are put to the test. There are two main ways that commodity prices are considered a leading signal of inflation. Often, economic developments can be seen in leading indicators before the overall economy feels them. Price inflation is expected to take hold by the time it reaches the end-user.

As per the market's circumstances, retailers must usually develop acceptable sales strategies to avoid oversupply or supply–demand mismatch, which might jeopardize their commercial concerns and possibly their existence, suggested by Guha et al.[23]. These plans were generally based on sales prediction, although they are not always. As a result, whether or not the commodity sales estimate was correct directly impacted the enterprise's revenue and expenses and its existence and growth.

Recently, sustainable businesses have begun to adopt computational and scientific forecasting technologies, using previous sales data to estimate future short-term or long-term product demand [24]. Market strategies that redefine service were becoming increasingly essential as traditional advertising gives way to customer relationships. For a company to be successful, it must master advanced forecasting technologies to address issues and take the initiative to assist customers [25]. Elements that contribute to a company success include preparation is the first step toward success, tenacity, the knowledge that one's achievement or failure isn't final, a sense of camaraderie and a common purpose motivation, making full use of the given resources, understanding of time, money, and resources is essential.

To make a product's marketing plan, evaluate all future elements, use a matured prediction approach and use quantitative statistics to estimate how the company can sell in the coming years suggested by Al-Weshah et al. [26]. In conventional analytics, companies relied mostly on qualitative predictions and basic regression analysis for predicting. The fundamental flaw of qualitative forecasting is that it relies too heavily on subjective and lacks facts backing it up [27].

Although the regression analysis approach was well-established in classical statistics, its versatility was limited, and its predictive precision was not particularly high. Thenon-stationary data analysis techniques and system identification were used to anticipate the issues and relied on standard mathematical and statistical methods with limited flexibility [28,29]. An early warning system based on non-stationary data analysis and system identification was put in place to identify potential problems before they even arose. As a rule, it is impossible to model or predict non-stationary data. Using non-stationary time series can lead to findings that show a correlation between two variables that do not exist, which can be misleading.

In CRM, customer satisfaction was created via proactive efforts to establish and sustain long-term consumer relations. An important part of CRM's concept was to make the whole organization customer-centric, which means that encounters with consumers must be regarded in the perspective of remains consistently suggested by Hargreaves et al. [30]. It was suggested that long-term relationships are maintained by structuring the firm around consumers, responding to their changing requirements, and delivering value to them as those needs change.

They defined CRM as a complete plan and strategy for gaining and keeping customers and building partnerships to produce greater value for the business's and consumers' interests. As part of this, the company's sales managers worked together with customer service representatives and supply-chain managers to improve customer value delivery efficiency and productivity [31]. As demonstrated in this research, the responsible member of CRM aimed to improve business performance and increase mutual value for the stakeholders associated with the connection.

Because organizations only have scarce resources, CRM emphasized the need to allocate resources depending on the business's lifetime worth of each client, suggested by Guerola-Navarro et al.[32]. This strategy process involved identifying the consumers that a corporation can economically service and structure the relationship between the organization and these consumers, to maximize the business's present and future value from consumers.

According to scholars, consumers' lifetime profit margins were used to assess and prioritize consumer connections, who recommended that a business's profit margins be increased by evaluating and prioritizing customer connections based on consumer profit margins [2]. Strategic CRM focused less on establishing and retaining connections and creating the right interactions that increase financial performance.

CRM was not just a technology or technique that helped firms develop customer connections. CRM is much more than just a part of technology. CRM configurations failed when CRM techniques were viewed as a limiting factor. And therefore, the effectiveness of CRM initiatives was not guaranteed by incorporating CRM technologies into an organization's processes or procedures.CRM was not just an IT solution used to recruit and develop a consumer base, suggested by Winer et al. [33]. According to scholars, CRM needs to be seen as an integral part of a larger strategic framework, and customer value must be enhanced in a planned and comprehensive manner.

Several additional experts were working in this field. Individuals' commodity choices and consumer habits were rapidly evolving. For example, the retail business saw increased prices for items and a wider range of modifications, speeding the sales revenue development pattern [34]. In the operation of commodities prediction, these new conditions lead to the effect of various elements, such as the fast change in business need, popular tendency, market prices, etc. It was important to consider promotional strategy and comments from data evaluations on different selling platforms when selling online.

To encourage transactions and improve production performance, it was crucial to anticipate the sales position of items, understand the production and consumption position, and create dependable approaches for business economic decision-making and business strategies correctly and reliably. A solution must be found quickly to assess all types of sales affecting variables and efficiently use past sales information to determine accurate predictions of future sales revenue. Variable pay is the portion of sales compensation based on an employee's performance. Bonuses, incentives, or commissions can be given to employees when they meet or exceed their targets. If an employee doesn't accomplish their goals, they will still receive their base income. This research, therefore, proposes an AI-CRM technology to address the challenges found from this comprehensive literature study [35].

Proposed AI-driven customer relationship management (AI-CRM) technology

CRM ideas have emerged due to declining customer loyalty in many sectors. The definition of CRM is it is an interaction strategy that bridges the gap between business investments and consumer pleasure to maximize profitability. To do so, it needed to:

- It acquires and updates knowledge about client requirements, incentives, and behaviour throughout a relationship.
- By learning from mistakes and successes, consumer knowledge can be used to enhance performance constantly.
- An organization's advertising, marketing, and service operations are coordinated toward a shared objective.
- The installation of suitable systems supports consumer knowledge gathering, sharing, and evaluation.

CRM needs a strong connection of customer-facing business operations to merge marketing, selling, and support services into one integrated system. Because these CRM procedures are semi-structured, they could be largely computerized and not formally specified. As a result, their productivity is heavily impacted by their information about goods, marketplaces, and consumers. Processes involving CRM might be characterized as knowledge demanding. CRM procedures require Knowledge Maintenance (KM) to handle the gathering, storing, and dissemination of specific knowledge. Their productivity is greatly influenced by their knowledge of the marketplace's items, markets, and consumers. CRM software also boosts sales floor efficiency by allowing staff to learn faster, respond more quickly, and sell more effectively. Incorporating a company's marketing efforts into the checkout process using CRM retail software is possible.

To satisfy current demands and generate new possibilities, Information Management involves identifying and utilizing knowledge resources that have already been obtained and existing assets acquired. The next section covers CRM and KM procedures to maximize CRM's capabilities and the closed information loop that should be accomplished.

Processes

As part of a collaborative research effort with numerous German and French financial institutions organizations, the structure described here further evolves from previous architecture. Six financial institutions participated in seminars in which the design was debated and verified in four-team sessions involving eight CRM and KM specialists.

The process architecture of the proposed AI-CRM technology is illustrated in Fig. 1. It has performance management and customer process. Operations are included on the application layer since they are considered important to CRM in most reviewed research. The system-level illustrates CRM-relevant information technology and its interrelationships.CRM's focus on customer interactions is a key component. When a customer has to complete a series of activities to fulfil a demand or address an issue, such as constructing a bridge, this is called the customer procedure.CX and CRM technology, like AI, augmented reality, virtual reality (AR and VR), and the Internet of Things, can be utilized to your advantage. More than ever before, CRM systems have grown to be more accurate and precise. Incorporating CRM and Predictive Analysis allows companies to understand better their customers' wants, needs, and habits. Gartner forecasts the CRM industry will rise at a compound annual growth rate of 13.7 percent (CAGR).

For a resource provider to fully cover a customer procedure, a client's process determines the necessary goods and resources. Cooperation with other resource providers who offer similar products or activities is important since most service suppliers cannot or don't want to handle the complete customer experience. CRM procedures can be divided into three classifications:

- Processes for the supply of CRM

Customers are directly involved in marketing campaigns, client services, managed services, and complaint strategic planning.

- CRM support procedures

Direct customer-contact operations that are not intended to cover a customer transaction and assist other CRM activities, such as market analysis and loyalty administration.

- Processes for analyzing CRM data

Processes that aggregate and evaluate client information gathered through other CRM operations are known as CRM knowledge management operations. The research findings enhance customer score and lead administration, customer profiling and classification, comments, and information sharing. Maximize sales and marketing synergy, decide on a persona for the buyer and one for the consumer, determine a threshold for lead scoring, recognize good behaviour by customers by awarding them points. Here, the inclusion of flaws improves.

Processes for the supply of CRM

In contrast to marketing relationships, relationship management is focused on interactive, personalized connections. In relational marketing, the main marketing procedure is campaign administration—marketing operations directed towards existing or potential consumers that are planned, carried out, monitored, and controlled. Advertising campaigns are personalized (one-to-one advertising) or segment-specific, employ different methods and enable recipients to provide comments through at least one communications platform.

- Marketing campaigns are designed to produce lucrative prospects or leads that are subsequently qualified via lead administration and are employed in sales. In the consumer process, instructional design handles articulating client needs.

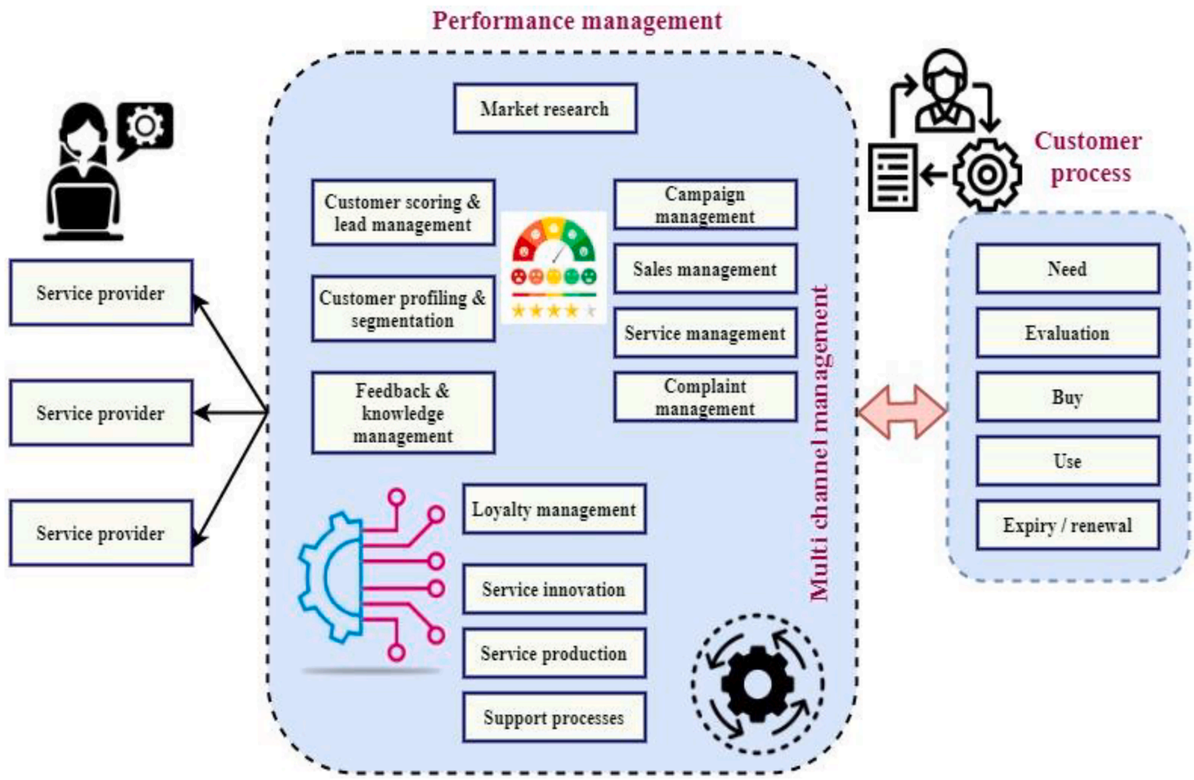


Fig. 1. Process architecture of the proposed AI-CRM technology.

- Client demands are best understood by consulting with a present or potential (but recognized) consumer and then submitting an offer and closing a contract. Consumer process steps of articulation, assessment, and purchase are covered by digital marketing.
- When it comes to customer processes, services and feedback management are complementary. Service administration is the process of designing, implementing, and monitoring services. After-sales activities such as contract administration and informational services are samples.
- Complaint administration is receiving, processing, and communicating customers' expressed discontent inside an organization. By immediately resolving concerns, the short-term goal is to enhance consumer satisfaction, and however, the goal is to prevent problems through a comment management procedure in the long term. This step of the consumer process is where complaints are most likely to occur.

CRM support processes

As a corporate marketing situation changes, the market experiment is intended, collected, analyzed, and reported. Managing client loyalty includes designing, implementing, controlling, and evaluating methods to maximize consumer connections' length and complexity. For example, regular flyer programs, loyalty programs, and churn monitoring detect consumers at risk of transferring to rivals at a preliminary phase.

CRM analysis processes

In lead management, interactions with prospective consumers are consolidated, qualified, and ranked in priority order. Campaign administration or other sources, such as the project management procedure, contact it with information. To give sales personnel a verified and prioritized list of potentially important prospective clients to be handled accurately and efficiently in the sales administration procedure. On the other hand, consumer scoring aims to compile a list of existing consumers interested in a certain product and service instead of lead administration. Asking the right questions will give you a better idea of whether or not a potential client is a suitable fit. Find out if they fit your target demographic and if the person talking to has the authority to make purchasing decisions. Use lead scoring to sort your sales prospects into several categories. Lead scoring is used to score prospects based on their perceived value to the business. The premise is the same, regardless of the method used by a particular firm.

That allows for cross-selling opportunities with current consumers and a more targeted approach to reducing contact expenses and enhancing consumer satisfaction. In consumer profiling, existing knowledge about consumers is analyzed to categorize and describe each client, their worth to the firm, commitment, interests for goods and interaction methods, and other characteristics.

Consumer profiling is used in marketing campaigns, sales governance, managed services, complaint handling, and loyalty managerial procedures. The fragmentation aims to create homogeneous client segments with different product and service requirements, and a business's customer requirements portfolio is based on customer segmentation. A company's clients are segmented so that they are comparable to one another, a procedure called customer segmentation. To get the most out of each client, a company should segment its customers to determine how best to interact with the various types of customers. In terms of time, money, and other resources, segmentation helps marketers be more effective. Market segmentation enables businesses to learn more about their consumers.

As part of CRM delivery procedures, including complaint administration, feedback managerial consolidates and analyses client knowledge. The goods, operations, and procedures of a firm are continually improved due to the outcomes. That is a cross-functional operation accountable for synchronizing CRM delivery and support operations. It is the integrated creation and management of goods and information transfers to and from consumers through various technology and communication platforms.

Implementing a tight information loop is crucial to good CRM. The CRM delivery and service operations must transfer consumer experience to the research methods. The analysis takes place there, and suggestions are provided to the distribution and support procedures. Information should only be gathered and evaluated if it is required to make suggestions.

All CRM procedures are managed through organizational performance, part of the overall CRM project management. It allows for integrated assessment, management, and allocation of resources to CRM operations. Based on activity-based costs (ABC), effectiveness monitoring determines the profit contributions produced by consumers and actions within CRM procedures.

Systems

CRM platforms, knowledge maintenance systems, enterprise resources planning (ERP), and national telecommunication are divided into three groups at the hardware level. CRM platforms, according to toMetaGroup, are divided into three divisions.

Implementing operational CRM systems increases the effectiveness of the distribution and supporting procedures for CRM services. Advertising, sales, and service automated solutions such as campaign administration systems and consumer engagement centres are included.

Quantitative CRM systems collect, store, and analyze consumer information to understand each client's behaviour better. The use of these tools consequently aids the CRM analysis procedures. Database, online analytic processors (OLAP), and data gathering platforms are examples of such systems. Customers' connection points and online communications are managed and synchronized by CRM systems that work in collaboration (e.g., telephones, email, and website).

The system-level architecture of the proposed AI-CRM technology is shown in Fig. 2. It has three CRM modules: analytical, operational, and collaborative CRM. Data such as client contact details and master data is processed by CRM systems. Documentation (formal information) and workers' implicit understanding are examples of less organized information KM systems allow to gather, share, and apply. The CRM distribution process relies heavily on this information to meet client demands. To provide consumers with efficient counsel, the sales manager must thoroughly understand the items provided. Document used by companies to track and complete a customer purchase Data capacity and user count can be scaled up without sacrificing performance. CRM software that uses social media and social media strategies to engage a company's client base is social CRM.

Four types of knowledge management systems are distinguished:

Content: The technologies in this category include document managing software (DMS) and content managing software (CMS).

Competence: Systematic management of workers' knowledge acquisition falls under this classification. Workers' competencies can be identified and made accessible via skill administration software and expert directory to assist the usage and growth of knowledge acquisition.

Collaboration: The employee cooperation module includes communication, processing, virtual community systems, and groupware software.

Composition: Systems, such as enterprise data retrieval platforms or gateways that structure, present, and locate knowledge fall under this technology area. ERP and transactional systems are extremely important to customer relationship management. Today's relationship marketing research encourages an examination of the effects of future behaviours, such as loyalty, performance, word-of-mouth collaboration, and communication, on factors of satisfaction, commitment, and trust through the study of these effects. Literature on customer relationship management (CRM) identifies three independent variables. Knowledgeability and two-way communication are the three most important factors to consider here. A bank employee's attitude toward their employment is referred to as their attitude in this paper for the sake of clarity. They collect and store organized customer information, such as consumer and contract data management, financial transactions, and other business observations. These data are required in CRM analytic procedures to have a comprehensive image of a client. However, CRM distribution and support procedures require access to all corporate information about clients to speak to them personally and better meet their demands.

Algorithm for optimizing neural networks components

The backpropagation-based neural network model is used in the proposed model. The AI-based learning techniques are used in the proposed model to enhance performance and reduce error.

Neural networking theory

That is a feed-forward system without response, called the neural network. Each level of neurons in the system is connected to the next layer through a link. Work is separated into two phases: learning and

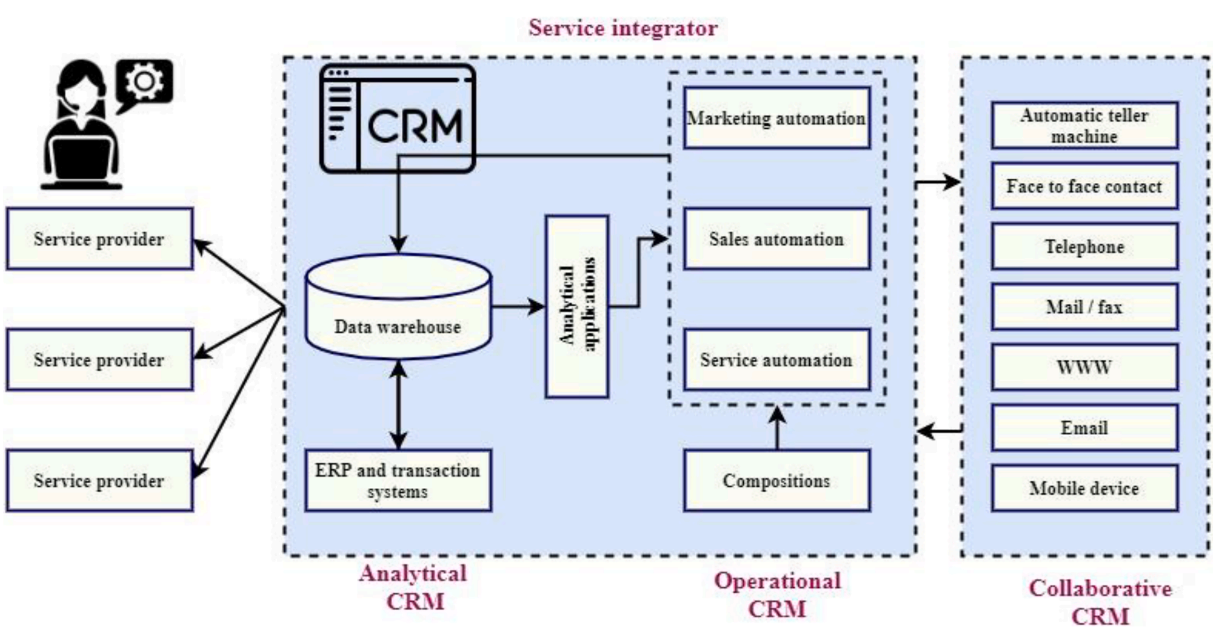


Fig. 2. The system-level architecture of the proposed AI-CRM technology.

testing. As a result of this mechanism, errors are propagated backwards in time.

3.3.2A neural network based on the Back Pressure (BP) model

The back pressure model is used in this section. A neural network model with three layers, namely input, hidden, and output layers, is present in the architecture.

The schematic view of the neural network is illustrated in Fig. 3. It has three layers, namely input, hidden, and output layer. This type of network depends on the complexities of the structure to handle the data. It can self-learn, and self-adapt.$x, y, andz$ represent the input level, hidden level, and output level neurons. Input standard function for each neuron's hidden level and output level are denoted in Eqs. (1) and (2). It is recommended that the number of hidden neurons be equal to 2/3 of the input layer's size and the size of the output layer. It is recommended that the number of hidden neurons be less than two times the input layer size.

$$n_y = \sum_{x=0}^{n} b_{yx} O_x \tag{1}$$

$$n_k = \sum_{y=0}^{n} b_{ky} O_y \tag{2}$$

Each neuron's outcome in the input level and output level are denoted $O_x andO_k$. The correlational weight present between input and hidden layer is denoted b_{yx} and the correlational weight present between hidden and output layer is denoted b_{ky}. To calculate the correlation coefficient, first, determine the variables' covariance and then divide the product of those variables' standard deviations by the correlation coefficient. A correlation factor is calculated for each layer to determine its effect on overall trustworthiness using a powerful correlation factor technique. A $+1$ or a -1 indicates a perfect correlation between any two variables. Correlation is positive when one variable rises in connection to the other, and it is negative when one falls in proportion to an increase in the other. Equations (3) and (4) express the input and hidden layer output.

$$O_x = f(n_y) \tag{3}$$

$$O_k = f(n_k) \tag{4}$$

The number of neurons present in the hidden and output layer is denoted $n_y andn_k$. Eq. (5) describes the unipolar Sigmoid variable activating feature $f(t)$.

$$f(t) = \frac{1}{1 - \exp(t)} \tag{5}$$

The error function is denoted in terms of *exp*, and the variable input of this function is denoted t.

3.3.3Calculate the error of the system

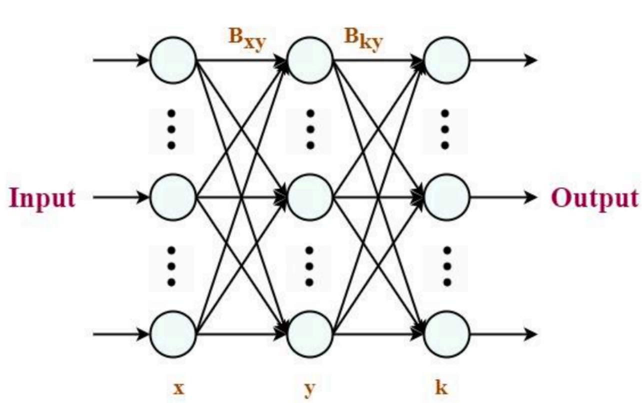


Fig. 3. Schematic view of the neural network.

As a result O_k of errors in learning, the platform's average error is greater than the network's outputs Y_k. The error present in a layer is denoted in Eq. (6)

$$E_r = \frac{1}{2}\sqrt{[O_k + Y_k]^2 - [O_k - Y_k]^2} \tag{6}$$

The outcome of the output layer is denoted O_k and the outcome of the hidden layer is denoted Y_k. Eq. (7) shows the network's overall error.

$$E_t = \frac{1}{2}\sum_{k=0}^{n}\sqrt{[O_k + Y_k]^2 - [O_k - Y_k]^2} \tag{7}$$

O_k denotes the output layer outcome and Y_k denotes the hidden layer outcome. The goal value of the BP neural networks is calculated. The error back-propagating technique minimizes the optimal solution during training.

Each layer weight of the system

Each level of the correction weights b_{kl} is a reversed operation, with the real output value Y_l and the real error message lis contrasted to both the hidden and output levels. Eq. (8) shows the particular layer's error message, and the respective correlation weight is shown in Eq. (9). Weight is a metric unit used to measure the strength of a link between two objects. Neuron 1 exerts a higher impact over neuron two if the weight from node 1 to node 2 is bigger, and weight reduces the relevance of the input value.

$$\beta_l = \frac{[Y_l - O_l]O_l}{[1 - O_l]} \tag{8}$$

$$b_{kl}(i) = b_{kl}(i-1) - \varphi\beta_l O_l + \tau\Delta b_{kl}(i-1) \tag{9}$$

The correlational weight is denoted b_{kl} and the error message is denoted β_l, the output message is denoted O_l. φ is denoted the training speed, and τ is denoted the velocity component. The hidden level error message l is communicated back to the input level, and the input level error message β_l is produced. Eq. (10) denotes the error message present in the input layer; the neural network contains too many weights, according to the error notice (i.e. the combination of variable levels is too high). Increasing the maximum number of weights in the model in the tool will allow you to modify the model's weights. And Eq. (11) denotes the correlational weight of the hidden and input layer. Cosine similarity between neurons' weight vectors is used to measure correlation in fully-connected layers, whereas filter matrices' cosine similarity is used in convolutional layers to measure correlation in weight.

$$\beta_l = \frac{O_l(1 - O_l)}{\sum_{k=0}^{n} O_k b_{yx}} \tag{10}$$

$$b_{yx}(i) = b_{yx}(i-1) + \varphi\beta_y O_x + \tau\Delta b_{yx}(i-1) \tag{11}$$

φ is the training speed, and τ is the velocity component, which improves the training pace of the BP neuronal networks and maintains a certain sense of predictability. The input layer outcome is denoted O_l and the output layer outcome is denoted O_k. The correlational weight between the hidden and input layer is denoted b_{yx}. The error message present in the hidden layer is denoted β_y. As a result of the training process, the connectivity weights among the network's components are fully defined, and the entire BP network has undergone an excellent learning experience.

Model building

The design of the proposed model using the BP model is done in this subsection. Each layer's weight and working procedures are explained below.

BP neuronal network variables determination

The three levels in the common BP neurological network are described below. Actual data in input and output layers and the number of nodes in hidden layers can be ascertained by the concept: the cell in hidden layers is greater than half of the incoming and outgoing layer - neuron quantity and less than the input and output level neuron amount. In terms of training effectiveness, the learning rate $\varphi \in (0, 1)$ and the movement term are important $\tau \in (0, 1)$.

Learning the network to determine the weights of the connections between each level

It's time to train the samples after selecting the model's variable. All training data must be re-trained to get network parameters between input and hidden levels and a connecting weight among the hidden and output levels.

The workflow of the AI-driven learning model is depicted in Fig. 4. The proposed AI-CRM model is trained using the dataset, and then the output/outcome is calculated. Using reverse calculation model error present in each layer is found. Based on the error, correlational weights are updated. An efficient learning approach for multilayer neuronal networks, the BP algorithm is among the most used learning algorithms. The major characteristic is forward signal transfer and reverses error propagation. It'sfeasible to achieve the learning goal by constantly changing the network's weight values. The BP algorithm is one of the most widely utilized methods for learning new things. In the chain rule, the backpropagation algorithm calculates the gradient of the loss function concerning each weight by iterating backwards from the last layer to eliminate unnecessary computations of intermediate terms in the chain rule.

Computation of the weight

The correlational value of the input and output is found in this subsection. Equation (12) and (13) shows the correlation rate present between input and hidden layer. Common representations can be learned using correlational neural networks (CorrNet). In terms of design, it's very similar to a traditional single-view deep autoencoder in many respects. Only one encoder-decoder pair is needed for each type of data to be encoded and decoded. For the hidden layer nodes, the sum of all input node values multiplied by their weights is used to calculate the hidden layer node values. The phrase "transformation" describes this

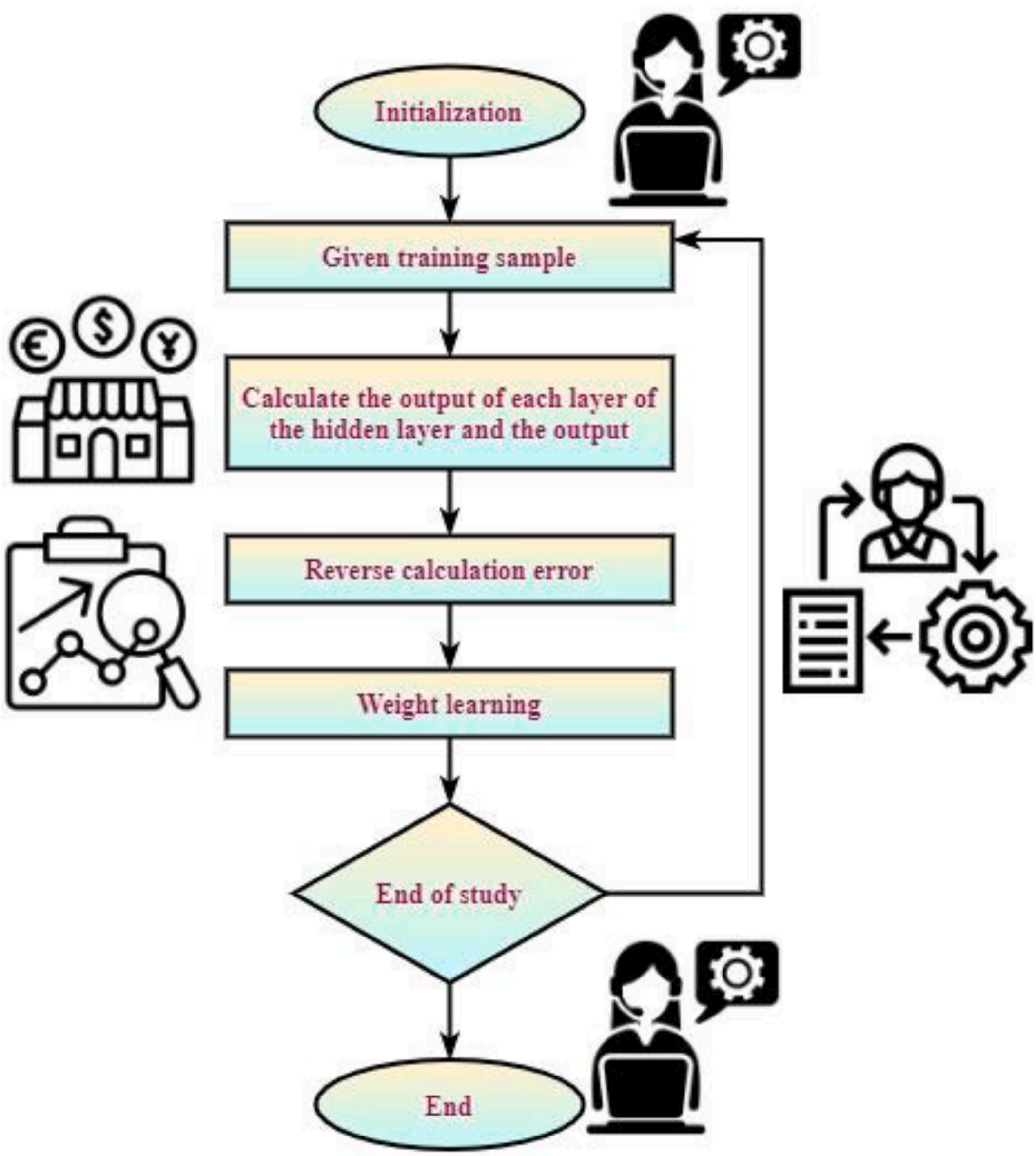


Fig. 4. The workflow of the AI-driven learning model.

phenomenon. When the summing is done, it includes the bias node with a weight of 1. Bias nodes can be used or not used.

$$r_{xy} = \sum_{k-1}^{K} \frac{b_{kx}(1 - \exp(t))}{(1 + \exp(t))} \tag{12}$$

$$t = b_{yk} \tag{13}$$

The data given to the input layer is denoted as t, and the value directly related the correlational weight present in the hidden and the output layer b_{yk}.

Eqs. (14) and (15) give the input and hidden layer correlation indicator. To determine the degree of connection between two or more measurements, one can use the Correlation Coefficient indicator. There is a stronger positive correlation when two instruments are trending in the same direction, whether up or down.

$$R_{xy} = \left\|1 - \frac{\exp(s)}{1 + \exp(s)}\right\| \tag{14}$$

$$s = r_{yk} \tag{15}$$

The correlational variable is denoted s. The correlation present between hidden and output layers is denoted r_{yk}. Eq. (16) gives the fundamental influencing factor.

$$S_{xy} = \frac{R_{xy}}{\sum_{i=1}^{n} R_{xy}} \tag{16}$$

The fundamental correlation indicator is denoted R_{xy}. The powerful correlation factor technique is used to calculate each layer's correlation factor to determine the effect of each indicator on universal trustworthiness. As a result of normalizing the link between input and output, the weight matrix of attribute B can be obtained. Eq. (17) shows the normalized weight matrix.

$$B = \frac{R_{xk}}{\sum_{k=1}^{n} R_{xk}} \tag{17}$$

R_{xk} is the correlation variable present between the input and output layer. The linear relationship between input and output can be obtained from this value. Some of the character descriptions are given below,

O_x	Input level
O_k	Output level
$f(t)$	Sigmoid variable activating feature
Y_k	Hidden layer outcome
b_{kl}	Correlational weight
β_l	Error message
φ	Training speed
τ	Velocity component

The proposed model is designed using a system model and process model. The relationship between input and output and the error present in each layer is found, and the errors can be reduced using the BP model.

Software analysis and evaluation

From April to August 2013, three Switzerland and German financial services businesses were studied. The location was chosen based on cooperation and the function and use of consumer information in CRM. That is why we concentrated on CRM in the consumer banking area of each company to assure consistency. Surveys with key respondents and content analysis of yearly reports, organizational charts, and systems graphs were used in all three situations to gather data.

Figs. 5(a) and 5(b) indicate the customer buying pattern analysis of the proposed AI-CRM model based on quantity and price, respectively. The analysis is done by considering the given dataset. Randomly 700 customer invoice is chosen from the dataset, and the respective quantity they have ordered and the price of the good are analyzed and plotted.

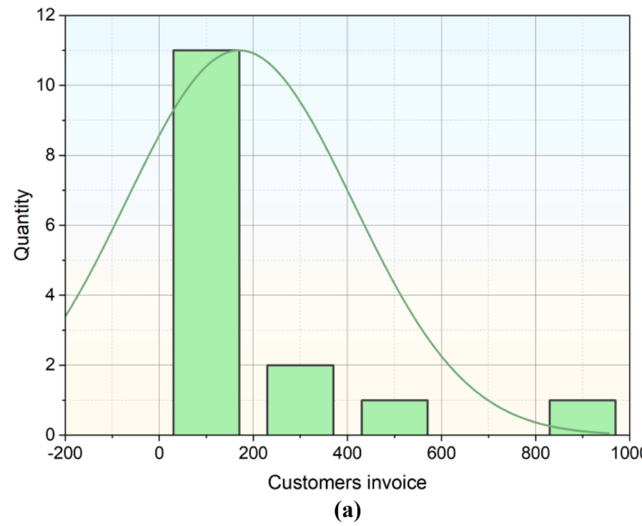


Fig. 5a. Customer buying pattern analysis based on quantity.

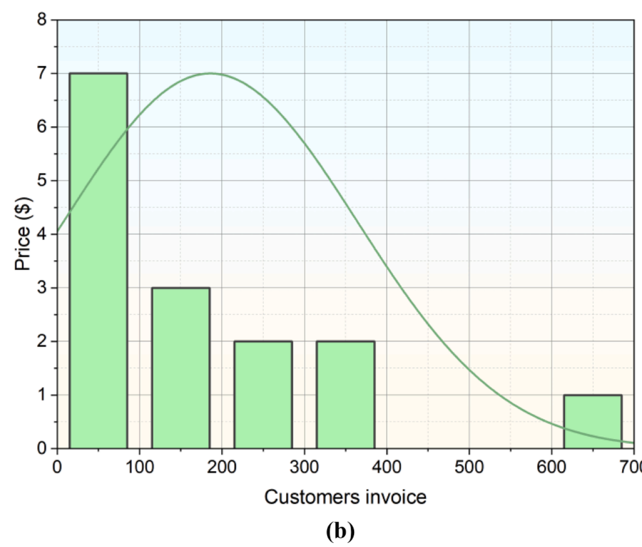


Fig. 5b. Customer buying pattern analysis based on price.

The results indicate that the majority of the consumers buy average price products with higher quantities, and consumers don't prefer higher prices or larger quantities of products simultaneously.

Table 1 denotes the consumer buying pattern analysis of the

Table 1
Consumer buying pattern analysis of the proposed AI-CRM model.

Customers invoice ID	Quantity	Price ($)
1	900	80
2	41	280
3	360	340
4	90	680
5	15	180
6	460	60
7	20	20
8	60	60
9	90	370
10	30	260
11	20	160
12	230	80
13	30	20
14	90	70
15	120	130

proposed AI-CRM model. From the given dataset, 15 consumer invoices are taken for testing purposes. The entire dataset is used to train the proposed AI-CRM model. The respective quantity and the price of those products are analyzed and tabulated. The results infer that most consumers' presser medium quantity items with lower prices, and very few prefer higher price products. So the proposed AI-CRM model is designed to produce cheaper products using AI technology.

The proposed AI-CRM model's training and testing error analyses are shown in Figs. 6(a) and 6(b). Ten samples were taken randomly for the training and testing in the given dataset. The respective predicted consumer behaviour is compared with the actual purchase of the same consumer, and the error between these are calculated and plotted. With the help of AI and the Backpressure model, the proposed AI-CRM model produces less error in both training and testing. The performance of the testing analysis is better than the training analysis.

Table 2 depicts the error analysis of the proposed AI-CRM model. A sample of ten customer invoices is taken from the given dataset, and the particular samples are used for training and testing. The predicted output of the proposed AI-CRM model is compared with the actual consumer buying pattern, and the error is calculated based on the deviation between these two values. Learning and testing are the project's two main components, and errors are sent to the beginning of time because of this system. The results indicate the proposed model produces higher accuracy with lower error because of the artificial intelligence and reverse error propagation model.

Figs. 7(a) and 7(b) show the training computation time and testing computation time analysis of the proposed AI-CRM model, respectively. The computation time is calculated as the total time required to produce the final consumer buying pattern. The simulation results show that the training needs more computation time than the testing model. Because the proposed AI-CRM models have the train, update the correlational weights, and based on the output, it has to update the correlational weights again once the initial setup is done. In contrast, testing the proposed AI-CRM model produces less computation time.

The proposed AI-CRM model is analyzed, the simulation outcomes are evaluated in this section. With the help of artificial intelligence and a fuzzy-based back pressure model, the proposed AI-CRM model produces higher results with lower computation time for the sustainable enterprise.

Conclusion and future scope

The current research aims to evaluate the customer experience (CX) for five AI-enabled products, including Product Recommendation systems, Virtual Agents, Email Marketing, Voice Recognition, and Visual Detection in terms of customer awareness, efficacy, and loyalty. It was found that:

(a)

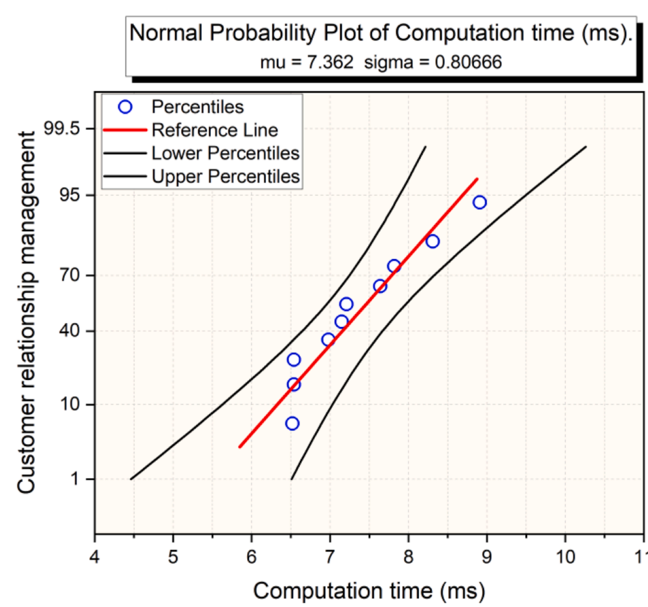
Fig. 6a. Training error analysis of the proposed AI-CRM model.

(b)

Fig. 6b. Testing error analysis of the proposed AI-CRM model.

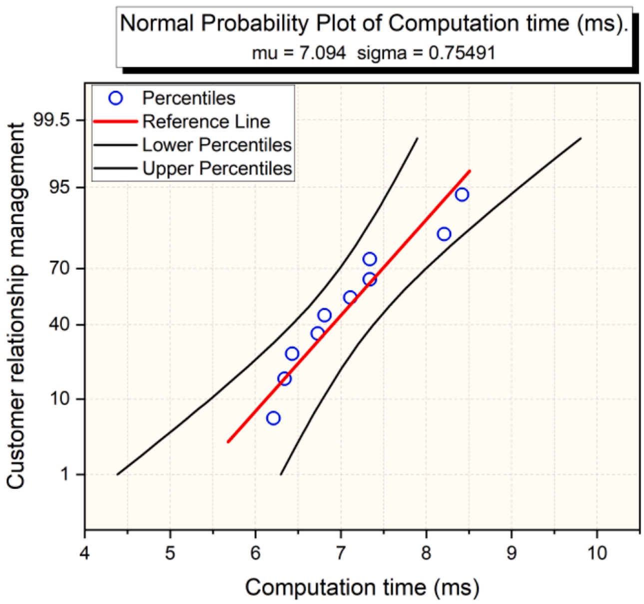
Table 2
Error analysis of the proposed AI-CRM model.

Customer ID	Training errors (%)	Testing errors (%)
1	19	21
2	48	46
3	81	72
4	86	76
5	47	42
6	24	21
7	46	39
8	41	31
9	63	54
10	18	12



(a)

Fig. 7a. Training computation time analysis of the proposed AI-CRM model.



(b)

Fig. 7b. Testing computation time analysis of the proposed AI-CRM model.

a) People are aware of the AI-enabled technologies they utilize on their different corporate sites.
b) AI-enabled technologies provide a pleasant customer experience (CX).
c) As a result, they remain loyal and continue to use these products, suggesting them to others.

AI-driven customer relationship management (AI-CRM) technology is proposed in this article. Academics and businesses are working together to discover and apply AI to benefit future commercial prospects. Potential business volumes can be improved by businesses delivering AI-enabled services to customers. As a result of AI, the studies suggest that current business can take on a new aspect in the coming years. Many businesses can struggle to survive due to AI's development, while many new businesses emerge.

Further studies might examine certain AI technologies and compare them to one other. In addition to AI-enabled techniques, such as the Internet of Things (IoT), CX researched using these methods. It is possible to study the demographic effect and connection in the future.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The research is supported by: National Natural Science Foundation of China, No.71472088; 71172104), the Research Fund for Young Teachers of School of Economics and Management, Nanjing University of Science and Technology (JGQN1702).

References

[1] Anshari M, Almunawar MN, Lim SA, Al-Mudimigh A. Customer relationship management and big data-enabled: Personalization & customization of services. Appl Comput Inform 2019;15(2):94–101.
[2] Foltean FS, Trif SM, Tuleu DL. Customer relationship management capabilities and social media technology use: Consequences on firm performance. J Bus Res 2019; 104:563–75.
[3] Zhao Y, Yu Y, Shakeel PM, Montenegro-Marin CE. Research on operational research-based financial model based on e-commerce platform. IseB 2021;1–17. https://doi.org/10.1007/s10257-021-00509-4.
[4] Chandrasekaran G, Nguyen TN, Hemanth D, J.. Multimodal sentimental analysis for social media applications: A comprehensive review. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery; 2021. p. e1415.
[5] Billah, M.F.R.M, Saoda N, Gao J, Campbell B. (2021, May). BLE Can See: A Reinforcement Learning Approach for RF-based Indoor Occupancy Detection. *In Proceedings of the 20th International Conference on Information Processing in Sensor Networks (co-located with CPS-IoT Week 2021)* (pp. 132-147).
[6] Ruan J, Hu X, Huo X, Shi Y, Chan FTS, Wang X, et al. An IoT-based E-business model of intelligent vegetable greenhouses and its key operations management issues. Neural Comput Appl 2020;32(19):15341–56.
[7] Abiad M, Kadry S, Ionescu S, Niculescu A. Customers' Perception of Telecommunication Services. FAIMA Bus Manage J 2019;7(2):51–62.
[8] Galiveeti S, Lo'aiTawalbeh MT, Abd El-Latif AA. Cybersecurity Analysis: Investigating the Data Integrity and Privacy in AWS and Azure Cloud Platforms. Artificial Intelligence and Blockchain for Future Cybersecurity Applications, 329.
[9] Dinesh Jackson Samuel R, Rajesh Kanna B. A programmable microscopic stage: Design and development. Microsc Res Tech 2019;82(4):429–42.
[10] Revathi S, Nagarajan B. Supervised sentiment classification using DTDP algorithm. Int J Sci Res 2015;3:645–8.
[11] Xu M, Peng J, Gupta BB, Kang J, Xiong Z, Li Z, Abd El-Latif AA. (2021). Multi-Agent Federated Reinforcement Learning for Secure Incentive Mechanism in Intelligent Cyber-Physical Systems. *IEEE Internet of Things Journal*.
[12] Gao Q, Guo S, Liu X, Manogaran G, Chilamkurti N, Kadry S. Simulation analysis of supply chain risk management system based on IoT information platform. Enterp Inf Syst 2020;14(9-10):1354–78.
[13] Gao J, Wang H, Shen H. (2020, August). Machine learning based workload prediction in cloud computing. *In 2020 29th international conference on computer communications and networks (ICCCN)* (pp. 1-9). IEEE.
[14] Manogaran G, Shakeel PM, Baskar S, Hsu C-H, Kadry SN, Sundarasekar R, et al. FDM: Fuzzy-optimized Data Management Technique for Improving Big Data Analytics. IEEE Trans Fuzzy Syst 2021;29(1):177–85.
[15] Karuppusamy P, Perikos I, Shi F, Nguyen TN. Sustainable communication networks and application. Lecture Notes on Data Engineering and Communications Technologies 2020:65–72.
[16] Wei W, Guizani M, Ahmed SH, Zhu C. Guest Editorial: Special Section on Integration of Big Data and Artificial Intelligence for Internet of Things. IEEE Trans Ind Inf 2020;16(4):2562–5.
[17] Gandhi UD, Kumar PM, Babu GC, Karthick G. Sentiment Analysis on Twitter Data by Using Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM). Wireless Pers Commun 2021:1–10.
[18] Chi J, Sui X, Alazab M, Muthu B. (2021). Cloud Computing based E-commerce Management Ontransaction Security Concepts.
[19] Chofreh AG, Goni FA, Klemeš JJ. Evaluation of a framework for sustainable Enterprise Resource Planning systems implementation. J Cleaner Prod 2018;190: 778–86.
[20] Amudha G, Narayanasamy P. Distributed location and trust based replica detection in wireless sensor networks. Wireless Pers Commun 2018;102(4):3303–21.
[21] Ameen ZJM. Secure Electronic Voting Application Based on Face Recognition and Ciphering. *Computer Engineering Department*. Baghdad, Iraq. ISSN Online: University of Technology; 2018. p. 2474–9257.
[22] Itani OS, Krush MT, Agnihotri R, Trainor KJ. Social media and customer relationship management technologies: Influencing buyer-seller information exchanges. Ind Mark Manage 2020;90:264–75.
[23] Guha S, Harrigan P, Soutar G. Linking social media to customer relationship management (CRM): a qualitative study on SMEs. J Small Bus Entrepreneurship 2018;30(3):193–214.
[24] Guerola-Navarro V, Oltra-Badenes R, Gil-Gomez H, Gil-Gomez JA. A research model for measuring the impact of customer relationship management (CRM) on performance indicators. Economic Research-EkonomskaIstraživanja 2021;34(1): 2669–91.
[25] Rodriguez M, Boyer S. The impact of mobile customer relationship management (mCRM) on sales collaboration and sales performance. J Mark Anal 2020;8(3): 137–48.
[26] Al-Weshah GA, Al-Manasrah E, Al-Qatawneh M. Customer relationship management systems and organizational performance: Quantitative evidence from the Jordanian telecommunication industry. J Mark Commun 2019;25(8):799–819.
[27] Chatterjee S, Ghosh S, Chaudhuri R. Adoption of ubiquitous customer relationship management (uCRM) in an enterprise: leadership support and technological competence as moderators. J Relatsh Mark 2020;19(2):75–92.
[28] Das S, Mishra M. The impact of customer relationship management (CRM) practices on customer satisfaction. In: Business governance and society. Cham: Palgrave Macmillan; 2019. p. 43–54.
[29] Cricelli L, Famulari FM, Greco M, Grimaldi M. Searching for the one: Customer relationship management software selection. J Multi-Criteria Decis Anal 2020;27 (3-4):173–88.
[30] Hargreaves I, Roth D, Karim MR, Nayebi M, Ruhe G. Effective customer relationship management at ATB financial: a case study on industry-academia collaboration in data analytics. *Highlighting the importance of big data management and analysis for various applications*. Cham: Springer; 2018. p. 45–59.
[31] Khashab B, Gulliver SR, Ayoubi RM. A framework for customer relationship management strategy orientation support in higher education institutions. J Strategic Marketing 2020;28(3):246–65.

[32] Guerola-Navarro V, Oltra-Badenes R, Gil-Gomez H, Fernández AI. Customer relationship management (CRM) and Innovation: A qualitative comparative analysis (QCA) searching for improvements in the winery sector's firm performance. Technol Forecast Soc Chang 2021;169:120838.

[33] Winer RS. (2020). An Updated Framework for Customer Relationship Management. In: The Routledge Companion to Strategic Marketing (pp. 56-66). Routledge.

[34] Oluwajana D, Adeshola I, Olowu G. Do the customer relationship benefits influence expectation of continuity? Adoption of social customer relationship management to promote eco-friendly products. *Journal of Public Affairs*, e2701.

[35] Tehseen S, Qureshi ZH, Johara F, Thurasamy R. Assessing perceived business success as a reflective-formative (Type II) second-order construct using PLS-SEM approach. J. Sustain. Sci. Manag 2019;14(5):84–114.