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Predicting Consumption Intention of Consumer Relationship Management Users Using Deep Learning Techniques: A Review

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A B S T R A C T

Consumer/customer relationship management (CRM) can potentially influence business as it predicts changes in people's perspectives, which could impact future sales. Accordingly, advancements in Information Technology are under investigation to see their capabilities to improve the work of CRM. Many prediction techniques, such as Data Mining, Machine Learning (ML), and Deep Learning (DL), were found to be utilized with CRM. ML methods were found to dominate other approaches in terms of the prediction of consumers' intention to purchase. This review provides DL algorithms that are mostly used in the last five years, to support CRM to predict purchase intention for better product sales decisions. Prediction criteria related to online activities and behavior were found to be the most inputs of prediction models. DL approaches are slowly applied within purchase intention prediction due to their advanced capabilities in handling large and complicated datasets with minimum human supervision. DL models such as CNN and LSTM result in high accuracy in prediction intention with 98%. Future research uses the two algorithms (CNN, LSTM) compiled to make the best prediction consumption in CRM. Additionally, an effort is being made to create a framework for predicting purchases based on many DL algorithms and the most pertinent characteristics.

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1. INTRODUCTION

This section is split into two significant parts emphasizing the context of this literature review and the main research contributions. Section 1.1 focuses on explaining customer relationship software and its importance to the business. Section 1.2 explains the motivation and contribution of this study.

1.1. Background

Customer relationship management (CRM) is a significant tool for serving the business. CRM's purpose is to preserve good relationships with customers during and after purchasing. However, the recent changes in the world have opened the marketspace in front of people with endless choices of purchase. Moreover, social media allows people to share their life experiences; including purchase experiences; which allows people to know a lot before conducting any transaction. Therefore, CRM is expected to cope with those changes to be a competitive benefit for the business. People share and exchange information about products and purchase experiences online, which makes the cost of a bad purchase of one customer serious as it could be disseminated online and seen by millions of people.

The advancements in IT have intensely changed the transmission of information and have resolved the outdated restraints of Word of Mouth (WOM) via emerging social networking sites (Hui, 2017). WOMs no longer carry out in restricted connection of face-to-face settings, counting single source and single recipient. Rather, WOM now progressively takes place in the more translucent public domain of the online community (Dwivedi *et al.*, 2021). The importance of WOM in influencing consumer purchase intention has been highlighted in many studies such as (Al-Nsour, 2017; Ismagilova *et al.*, 2020). On other hand, recognizing the potential consumers matters a lot for the growth of companies. This possibility can be estimated well earlier based on numerous factors such as the consumer's opinion regarding the products before the actual sale is started. Accordingly, online sales points should be armed with tools to collect information that help the future purchase of consumers.

Social media has significantly influenced the way businesses to look at customers' intentions (Perez-Vega *et al.*, 2022). Social media currently become an inevitable platform of marketing and a great source of a pile of consumer data (Ahmad *et al.*, 2020) that can enhance the functionality of CRM in terms of foreseeing the future (Perez-Vega *et al.*, 2022). Therefore, traditional CRM that classically require IT staff to keep tracking changes in customers' data related to their purchasing behavior; is losing the race and encountering serious challenge in terms of accuracy and p5erformance (Perez-Vega *et al.*, 2022).

CRM employment in business was sharply escalating in the last three decades (Arora *et al.*, 2021; Stokić *et al.*, 2019). However, the upsurge of social media and its use as a platform for marketing, selling, and customer services has reduced the isolated management of CRM and enforced it to mainly accept and analyze data coming from social media to foresee future changes in customers' behavior and intention. The trend among researchers now is to use the terms Social CRM (SCRM), which implies the enormous changes taking place in the domain of SCRM (Perez-Vega *et al.*, 2022). For example, using SentiGem API, research has been done to analyze reviews such as from Twitter (Granados *et al.*, 2022) to extract opinions and sentiments about a set of products (El Fazziki *et al.*, 2017).

Customers' satisfaction and churn are indicators of the good economic health of the firms and indicate their competitiveness (Mahalekshmi & Chellam, 2022). Excellent CRM management has a significant influence on the innovation of business bodies (Ayyagari, 2019; Migdadi, 2021). Then,

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customers churn, or satisfaction is the key point of CRM (Mahalekshmi & Chellam, 2022). This means employing state-of-art tools and techniques with CRM will eventually benefit firms in terms of understanding customers and introducing innovation in services and products. Migdadi (2021) has positioned CRM between Knowledge management and innovation capabilities, the flow of information and knowledge must go through CRM to maintain high competitiveness. Though there are many sophisticated techniques employed in CRM such as information sharing, customer involvement, long-term partnership, and joint problem solving; they mainly work with historical information; which could be a pile of data (Ayyagari, 2019).

The lack of foreseeing the near future with customers in CRM could be mitigated when the latest advancement in Artificial Intelligence (AI) and machine learning are employed. Deep learning is a recent advancement in the AI field (Zhu *et al*., 2021) and could benefit from the pile of data collected in CRM to predict changes in the intentions of customers (Mahalekshmi & Chellam, 2022). This has numerous benefits that make firms ready for changes in the future and change their marketing strategies to fit with changes in the customers' intentions. This work investigated the current advancements and challenges of employing deep learning and machine learning in predicting consumers' intention to purchase within the context of CRM or/and online business.

1.2. Research Highlight & Contribution

This review papers include the most practical articles that used Deep Learning algorithms to predict the consumption intention of CRM users. The paper includes different methods that have been studied to predict the intention with or without CRM software and lists them in **Table 3**. Then, the most practical papers that used Deep Learning with CRM users were listed in the discussion section **Table 4**. This study reviews the most common algorithms that are used in the existing literature. The study summarizes Deep Learning applications on CRM as many previous studies focus generally on Deep Learning applications [65]. To achieve this objective, this research focuses on the main keywords which are predicting intention with CRM users and how deep learning involve the intention by comparing it with other algorithms. The paper focuses on predicting the intention for CRM users and compares the deep learning algorithms with other methods.

Furthermore, this study focused on reviewing articles that use Deep learning models for the prediction of the consumption intention and classifies the features that support the easy prediction. Lack of research on the role of deep learning techniques used in various CRM dimensions such as in predicting the consumption intention of CRM users which is the main focus of this study hinders a deeper analysis.

However, there are some studies conducted in this domain. A systematic review by Neu *et al.* (2022) studies the process prediction approaches proposed and data pre-processing techniques. However, the review article mentions the advantages and disadvantages of existing approaches for process prediction generally without focusing on specific domains. Velu (2021) examines how ML techniques are used in customer relationship management; however, the review is brief as it does not mention the types of algorithms applied, and it lacks a comparative analysis of the studies.

The benefits of Machine learning techniques when applied to each CRM domain and element. However, it lacks a deeper analysis of the studies regarding the significant features used by researchers for easier prediction. Furthermore, it answers questions related to the techniques applied to CRM and the practical implications whereas this study goes deeper into understanding the current challenges in

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employing Machine learning and Deep Learning as well as the prediction criteria.

The paper is organized as follows, Section 2 focuses on the methodology adopted to perform review, whereby the research questions and inclusion and exclusion criteria are presented. Section 3 is covering the related work by reviewing the Customer Relationship Management software and how it supports business growing, then explaining the most used predicting criteria to study customer behavior in purchasing online products. The section focuses on the features used to predict consumption intention of customers to help decision making and increase market sell by understanding customer or a group of customers. The section reviews the predicting criteria and compares in detail. Section 4 explains Deep Learning algorithms and their applications like CRM, banks, airports, government works etc. Section 5 presents the results and discussion of the surveyed articles. The result section includes the most seven practical papers and Deep Learning algorithms used on this study that focused on customer behavior on predicating intention. Additionally, the discussion the results of this review is added to induce the research gaps and limitations, adding that most papers focused on the same domain. Finally, in section 6, our research is concluded by reviewing the importance and content of studies on predicting intention for business growth using state of arts based on Deep learning Algorithms, and suggestions for further work extracted from this review were provided.

2. METHOD

The study plan for achieving the contribution of this research was to focus on two parts: Section 2.1, focus on the questions that need to be answered to get the literature gaps. Section 2.2 collects the related works that match keywords in depend on inclusion and exclusion criteria that divide the main point for prediction purchase in CRM using Deep learning or other methods.

A literature review (LR) of many papers (Tranfield *et al*., 2003) was utilized in this work to find recent innovations in predicting consumers' intention to purchase. The purpose was to inspect the latest trends, technologies, and challenges within the field of CRM and its capability to predict consumers' purchase intentions. LR has several advantages, including identifying studies alone with reducing bias (Reim *et al*., 2015) and finding gaps in the current literature to determine the possible future research direction (Sharma *et al*., 2020). Henceforth, this work followed (Tranfield *et al*., 2003) and used a three-step process, (a) developing the research question, (b) specifying inclusion and exclusion criteria of selection, and (c) applying the review criteria for analysing the studies.

2.1. Research Questions

This review was targeting finding answers to questions such as what are the current works and challenges in employing deep learning and machine learning for consumers' prediction? Which algorithm type (machine learning or deep learning) is effective in prediction? And what are the prediction criteria employed?

2.2. Inclusion and Exclusion Criteria

The research was included when it analysed some aspects of consumers' purchase intention or behaviour. With these, research addressing both intention and the actual behaviour of CRM consumers was included; research from 2016 until 2022 were taken; research only in the English language was considered to evade biases related to language (Khanra *et al*., 2020); all research needed to be peer-reviewed. The exclusion criteria were that non-peer-reviewed studies were not included; studies that were not relevant to the domain were not considered in the study. As per the research questions, searching "consumer's purchase intention",

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"CRM", "deep learning" and "machine learning have been used as keywords in the title and abstract to obtain the inclusive set of studies for the review. The terms related to the name of machine learning methods (i.e., SVM, KNN, etc.) were not used as the keywords, as, the word machine learning is often used in the abstract along with the specific machine learning method used.

Peer-reviewed journals have been considered in the data search as they are more reliable and use rigorous scientific evaluation methods. Specifically, all the studies in ScienceDirect, IEEE Xplore, and Scopus were searched till August 2022 for this review. We have used ScienceDirect, Scopus, and IEEE Xplore because they are powerful in providing articles (Xiao & Watson, 2019). The idea is to collect articles that have been rigorously assessed and this ensures the quality of the results that are referred to in this study. These databases were employed so that this work can be made as inclusive as possible. A total of 460 study was retrieved-yet not filtered- as the search results of all three databases.

Then, important information about the studies found such as title, abstract, authors' names, journal name, and publication year were stored in the MS Excel spreadsheet. A total of 460 publications were checked for duplication of the paper or out of the scope of this work were eliminated, and a total of 680 publications were left. Then, after that, the initial screening process for the title, abstract, and conclusion was taken place to eliminate the studies that have not employed any prediction technique for consumer purchase intention, and a total of 200 publications were eliminated.

After these, 260 studies were left for full-text assessment, and these were wisely reviewed fully for assessing their eligibility for the study. For the sake of this study's objective, studies that applied machine learning or deep learning with data collected from online business websites, CRM, or real consumers have been considered. Besides that, studies that predict intention to purchase mainly have given priority; particularly when they use criteria that are accessible to other researchers and their models are replicable. In the last, 50 studies were reported in this work. These publications were accurately reviewed and assessed.

3. LITERATURE REVIEW

The following subsections present the current research that targets improving CRM quality in predicting consumers' intention to purchase. Section 3.1 describes CRM and what are the various data types used to predict consumers' intention to purchase. Section 3.2. reviews the features (prediction criteria used by existing researchers. Section 3.3 describes the data process of segmentation. The introduction to the concept of consumer purchase intention is mentioned in section 3.4. Furthermore, the subsection describes the concept of Deep Learning and its utilization in consumer purchase intention and CRM. This section compares the performance of Deep Learning and machine learning when used within the context of CRM and consumer purchase intention.

3.1. Customer Relationship Management (CRM)

Customer Relationship Management systems are employed to permit firms to obtain new consumers, begin an unceasing relationship with them and rise consumer retention for more profitability (Baderiya & Chawan, 2018). CRMs employ machine learning and deep learning to analyze data related to consumers' personal behavioral to give firms a competitive advantage by growing consumer retention rate (Cao *et al*., 2021). Those models can predict consumers who are anticipated to churn and the motive of churn (Baderiya & Chawan, 2018). Estimates are used to design targeted marketing plans and service proposals.

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Figure 1 shows that CRM tries to come up with a multi-modal, long-term view of the consumer for the mutual advantage of the consumer and the firms. Therefore, it is advisable to focus on short-term consumer intents such as purchase prediction or interaction with content, CRM uses a more holistic approach. CRM aims to understand the consumer's long-term and frequent motivations, in addition to short-term actions. Various approaches have been applied and tested.

Besides that, various criteria have been passed to the proposed models to assess their capabilities in predicting the purchase intention of the consumer. It could be seen that there are primary data are collected directly from consumers and secondary data collected from tracing consumers' activities online. Some researchers work on consumer prediction overall without consideration of the type of purchase, money spent, etc. Meanwhile, the other researchers divided consumers into segments in order to increase the accuracy of prediction for each segment of consumers based on their collective behavior online.

3.2. Prediction Criteria

Prediction criteria refer to a group of data collected either from consumers or based on their behavior during past purchase transactions. There are many features have been employed to predict the consumer's intention to purchase. Among them is the polarity (i.e., the sentimental status: positive, negative, or neutral) and "weighted like-to-dislike ratio" in YouTube, which have been used by (Ahmad *et al*., 2020). Other criteria; but from a survey of 401; are uncertainties in product quality and product fit that significantly and negatively predict the purchase intention, meanwhile automatic habit is positively predicting the purchase intention (Chen *et al*., 2022). Other criteria are more related to web browser activities by consumers. The data (browsing activities) collected have been categorized into purchase-oriented and general-sessions using extreme boosting machines. However, the dataset was unbalanced, i.e., The dataset has 9,249,729 anonymous browsing sessions, but 5.51% of those sessions lead to successful consumer purchases. In fact, the session contains product viewing and purchasing transactions are recorded. An unbalanced dataset (85% of records indicated no purchase) of online browsers' activities.

The above discussion has shown that features collected from browsers' sessions are dominating the research that discusses consumer purchase prediction. The session data collected from consumers' behavior on the browser seem reachable and affordable for CRM because those sessions within eCommerce platforms are provided by firms and integrated easily with CRM. It is also noticeable, the features that help in predicting intention to purchase in a physical environment where consumers interact with products are different from those collected online. **Table 1** summarizes the prediction criteria, data source, and business domain used by researchers. It could be seen that data collected from the online business regarding the consumer's activities online from the number of seconds spent on webpages to the number of clicks. Some researchers included demographic data such as gender. Age etc. into consumer's online activities for better prediction. Meanwhile, the works that used surveys have focused more on product quality in their purchase prediction of consumers. It was noticed that there is a large list of features; particularly online sessions; and many of them are less important. Therefore, there is a try to optimize the list of features. They used feature selection collectively with Adaptive Synthetic Sampling (ADASYN), which when combined with the random forest algorithm has improved the accuracy of the prediction. Optimize feature selection but this time by focusing on unique features of every product in order to understand better the intention of the consumers.

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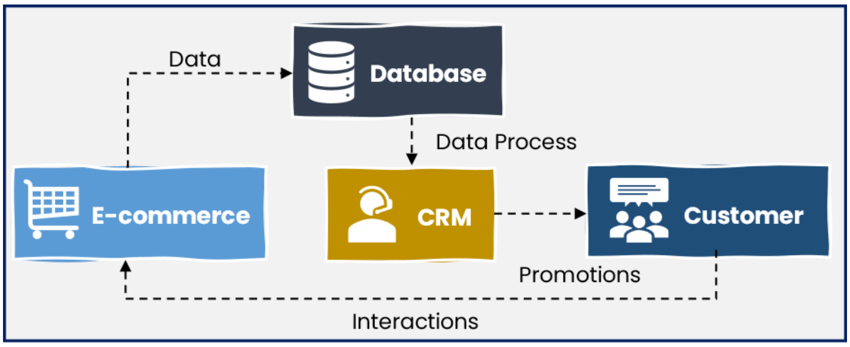

Figure 1. CRM in sales interaction.

Table 1. Prediction criteria used for consumer's purchase intention.

No	Ref. and Publication Year	Criteria	Data source	Industry
1	Chen *et al.* (2022)	Uncertainties in product quality, Product fit automatic habit.	401-survey	General products
2	Chakraborty and Paul (2022)	Social values, functional values, emotional values, conditional values, age, gender.	878 healthcare app users	Healthcare services/products
3	Chen *et al.* (2022)	N/A	23,432 passenger travel samples	Airlines
4	Cao *et al.* (2021)	Eye tracking data (Fixation, Saccade, Blink, Scanpath length, Pupillary response)	Apparel online website	Apparel
5	Esmeli *et al.* (2021)	Click events on an item associated with the session id, category and the timestamp, purchase events, price, and quantity of purchase.	Session logs from YooChoose-German SaaS provider.	Clothes
6	Chaudhuri *et al.* (2021)	Platform engagement and customer characteristics	50,000 unique web sessions	E-commerce
7	Liu *et al.* (2021)	The historical behaviour data of 100,000 users and user personal profile data.	JData dataset and the T-mall dataset.	E-commerce
8	8 Vaca *et al.* (2020)	Consumers' demographics and online user session attributes	Social Network Advertising Sells, Organic Purchased Indicator, and Online Shopper's Purchasing Intention	General products
9	Ahmad *et al.* (2020)	Weighted like-to-dislike ratio, polarity	YouTube	Movies
10	Baderiya and Chawan (2018)	Adaptive or dynamic pricing of a product, visit attributes, visitor attributes, purchase history, web data, and context understanding	Online shopping	E-commerce companies
11	Hui (2017)	Source Credibility by Consumer Purchase Intention	Survey of 120 Malaysian consumers	General products

** (N/A) denotes unavailable information; Based on the author's knowledge.*

Although, the accuracy was high (0.94), it will be impractical with products that come from thousands of sources such as apparel and food. A deeper proposal to handle the large dimensionality of features and incomplete data was proposed by Chen *et al.* (2022) with the airline industry. Another study has focused on processing data locally (Ahmed *et al.*, 2022), then servers perform aggregation for results in order to reduce communication costs while ensuring privacy. However, a such proposal can work in an

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environment where the internet of things is available for regular consumers, they are mobiles and laptops.

3.3. Data Process for Prediction Intention

There are two approaches found to process data entries in order to develop a prediction of a consumer's intention to purchase. Many studies have used segmentation, which means classifying training data into groups based on certain criteria (i.e., based on demographic data, purchase habits, browsing history, etc.). This simplifies the process of prediction based on aggregational values. Moreover, some researchers used segmentation to overcome imbalanced classes and develop a special model for each segment (Ren *et al.*, 2021). Another approach is a prediction based on an individual entry in the dataset. For instance, reference (Baderiya & M. Chawan, 2018) focused on consumer segments for predicting purchases rather than on individual consumers, however, their work was in progress, and less revealed.

3.4. Customer Intention to Purchase

Understanding consumers' purchase intention is significant for many reasons. Consumers typically signify <5% of all website visitors but contribute nearly all the profit. Then, firms should develop effective measurements to sport those consumers and target them with special offers, discounting, or enhanced advertising. Similar work was done by Ren *et al.* (2021), but this time with a coupon. Consumers were found to be segmented as potential e-coupons users, low discount-sensitive users, and high discount-sensitive users. Similar segmentation was done with credit card users (Ho *et al.*, 2021). Therefore, determining the behavior of visitors (who are potential buyers) of online businesses via their online activities and weblog is crucial. Moreover, the data collected from weblogs assist marketing forces in regularly utilizing such data to come up with an intelligent promotional campaign to convert regular visitors into paying consumers.

Purchase intention could be defined as the estimated behavior of a consumer regarding her/his future purchase decision (Ahmad *et al.*, 2020). The request for a product could be recognized by a number of opinions (online) viewed by consumers on social media (Ahmad *et al.*, 2020; Chen *et al.*, 2022; Ho *et al.*, 2021). The information posted on social media is active in rising other consumers' purchase intentions of a specific product as empirically found by Hui (2017). Consumer intention is an internal force of consumption behaviors and has a substantial role in perceiving and predicting consumers' demand and purchase. However, consumption intention prediction is challenging. Different from consumption behaviors, where consumption intention is implied and always not reflected by behavioral data. Additionally, it is influenced by both consumer's inherent preference and Spatio-temporal context.

Predicting the consumers' purchase intention is vital to the pertinent decision-making departments of brands (Vaca *et al.*, 2020). As e-commerce evolves, sales transactions generate necessary data forming a robust storage mechanism ready for analysis to further support strategic and timely decision making (Dahr *et al.*, 2022). Currently, studies consider social media as the source of data that crucially helps in predicting a customer's intention to purchase, since consumer looks to social media as a place to show opinions and share their experience with others (Ahmad *et al.*, 2020). For instance, movie makers can know in advance the success rate of their movies by predicting the sentiment values of people's comments regarding the movie trailer on YouTube (Ahmad *et al.*, 2020). Another approach to knowing the purchase intention of consumers was a survey (Hui, 2017), which was then processed using machine learning methods. The critical factors that were found

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to influence the intention to purchase; were product price and manufacturing date.

Worldwide, e-commerce websites are used by millions of people each day to make purchases. When users utilize e-commerce websites, a significant amount of click stream data is produced. The ability to predict purchase intent and learn about user behavior from click data has become crucial. Moreover, intention to continue using B2B e-commerce can be defined by the Perceived Usefulness (PU) factors such as information intensity which can significantly have an indirect effect (Hussein *et al.*, 2019). An approach for estimating purchase intention prior to concluding client sessions is suggested within the context of this study.

4. DEEP LEARNING

The main objective of this research is focused on Deep learning methods and their application on CRM. First, section 4.1 where deep learning is applied, and most algorithms on this application. Second, section 4.2 focuses on Deep learning algorithms with CRM application only. The utilization of machine learning to handle consumer interest prediction is a hot research paradigm in the field of business. The current advancements in artificial intelligence tend to focus on tailored deep learning procedures (Vaca *et al.*, 2020), i.e., dedicated to fitting specific domains. These procedures were reported to be mainly operative in vastly complex environments such as natural language processing, image processing, and stock price predictions. Companies invest a significant portion of their budgets in predicting consumer behavior to avoid uncertainty due to greater market volatility and discrepancies.

Several machine learning and deep learning techniques; have been found in literature; used to predict the consumers' satisfaction, intention, or churn with good accuracy (Mahalekshmi & Chellam, 2022). For instance, Vaca *et al.* (2020) developed several decision-tree-based models to prove that cheaper AI methods (i.e., decision tree) can provide high performance in terms of prediction. Similarly, Mahalekshmi & Chellam (2022) have compared the performance of Gradient Boost, XGBoost, AdaBoost, Logistic Regression, ANN, Random Forest, and deep learning (CNN, stacked auto encoders). They found deep learning techniques outperform other machine learning methods. In terms of machine learning methods, logistic regression has proven itself to be the accurate predictor of customers' behavior among k-nearest neighbors, bagged trees, Random Forest, AdaBoost, and extreme gradient boosting (Ren *et al.*, 2021). The following subsection covers machine learning methods and deep learning techniques employed in the business including CRM.

4.1. Deep Learning Applications

Applications that extend Microsoft speech recognition (MAVIS) for scanning audio and video data through human voices and talks increasingly rely on deep learning. The Big Data environment application used by Google for image search service and Google's Deep Dream is software that classifies images but also generates strange and artificial paintings based on its own knowledge (Ren *et al.*, 2021). Facebook also uses Deep learning beads text understanding engine, which can classify massive amounts of data, provide corresponding services for identifying users' chatting messages, and clean up spam messages (Ho *et al.*, 2021). Deep learning is used for several common areas where the most focused domain among research is computer vision, prediction, semantic analysis, natural language processing, information retrieval, and customer relationship management is one of the newer areas of application of deep learning (Ho *et al.*, 2021). Deep learning has shown high accuracy in other applications such as context-based recommender system (Achmad *et al.*, 2019) for restaurants (see **Table 2**).

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Table 2. Deep learning algorithms used for various applications.

#	Deep Learning Algorithms	Characters	Area Used in
1	*The Recurrent Neural Networks (RNN)*	Remembering prior inputs and employed in image captioning, time-series analysis, natural language processing, handwriting identification, and machine translation.	CRM, Image process, Airports, handwriting identification, and machine translation
2	*Convolutional Neural Network (CNN)*	Employed in image processing and object detection.	Medical (Szegedy *et al.*, 2014)
3	*Long Short-Term Memory (LSTM)*	Recall prior inputs that are helpful in time-series prediction.	Voice recognition, handwriting recognition, Banks, CRM (Hochreiter & Schmidhuber, 1997)
4	*Generative Adversarial Networks (GANs)*	The two components of GAN are a discriminator that incorporates the fake data into its learning process and a generator that learns to make false data.	Video game producers, 2D textures, and produce realistic visuals and cartoon characters (Goodfellow *et al.*, 2020)
5	*Radial Basis Function Networks (RBFNs)*	They are mostly used for classification, regression, and time-series prediction and contain three layers: input, hidden, and output.	N/A
6	*Multilayer Perceptron's (MLPs)*	Contain many layers of activation-function-equipped perceptron's.	Software for speech recognition, image recognition, and machine translation
7	*Self-Organizing Maps (SOMs)*	To provide data visualization by using self-organizing artificial neural networks to condense the dimensions of the data.	High-dimensional data
8	*Deep Belief Networks (DBNs)*	Generative models made up of a number of layers of stochastic latent variables. RBM layer interacts with both the layer above and below it because of connections between the levels of the stack of Boltzmann machines.	image, video, and motion-capture data.
9	*Restricted Boltzmann Machines (RBMs)*	Two layers are present in RBMs visible and hidden. visible is linked to every unit that is concealed. The only output nodes of RBMs are the bias unit, which is linked to both the visible and hidden units.	Handwritten Digit Recognition
10	*Autoencoders*	These trained neural networks repeat the data from the input layer to the output layer.	Image processing, popularity forecasting, and drug development

** (N/A) denotes unavailable information; Based on the author's knowledge.*

4.2. Deep Learning and CRM Application

As has been discussed above, CRM now needs to handle the pile of data that exist in social media and considerably carry themes that could reveal future changes in consumers' intention. Therefore, CRM is required to utilize powerful tools that can easily process the pile of data and build a prediction system. This is possible with the emergence of AI and deep learning (Chatterjee *et al.*, 2021). The model proposed by Chatterjee *et al.* (2021) has come with

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findings that reveal how significant to employee deep learning for the sake of enhancing the quality of CRM. Moreover, Liu *et al*. (2021) emphasized that Deep Learning outperforms traditional machine learning methods in predicting purchase intention. For instance, developed a deep learning model that successfully predict 98% of consumers' intention to purchase. Many evidence showed that deep learning has competitiveness over machine learning in some specific business tasks, in particular, the task of predicting consumer purchase tendency which is a significant issue in online business.

Churn data model using Deep learning created by (Seymen *et al*., 2021) the model was compared with logistic regression and artificial neural network models that used also at churn prediction studies. The result on (Seymen *et al*., 2021) model found that deep learning model achieved better classification and prediction success than other compared models.

The study by (Velu, 2021) focused generally the advantage of using Machine learning at CRM system. His study method was pivotal in in answering questions: how and why machine learning and its techniques are used in CRM. Machine Learning has several algorithms (Amnur, 2017) used Support Vector Machine (SVM) to identification the active and nonactive customer at bank to increase the relationship and interactions with customer.

The amount of data created by typical users has greatly increased as the digital age has progressed. This expanding data has a variety of uses, including helping businesses and governments better manage resources and provide more individualized services, and companies can utilize it to select the best candidates for a job. While these applications may seem extremely enticing, a couple of problems must be solved first: collecting data and analyzing it to draw out useful patterns. These issues are addressed, respectively, by the disciplines of big data and data mining. Even if they can complete tasks without explicit programming, computers nonetheless think and behave like them, which is why machine learning describes them. Due to their precise modeling of the human brain, deep learning models provide a very sophisticated approach to machine learning and are prepared to take on these difficulties. Users are charged for 8 to 9 tries per day; hence visiting the cloud 8 to 9 times is necessary to lower this number. Additionally, SVM outperforms random forest prediction techniques by up to 75%, assessing user behavior based on billing logs to increase income while maintaining resource efficiency (Ibrahim *et al*., 2018).

Additionally, businesses lack churn forecasts to keep customers. This issue has an impact on both the company's revenue and its ability to grow. One of the most important tasks for the business is to keep its current customers. As technology advances quickly, new machine learning and deep learning techniques are developed that telecom businesses may employ to track customer churn behavior.

The results suggest that online review platforms should create a scalable image and text-processing algorithms to identify the reviews that are the most helpful and enjoyable. In order to guarantee that customers see more positive reviews and photographs with good emotions, reviews might then be filtered in accordance with this information. Increased search expenses for customers and a challenge for management are both brought on by the growth of a big volume of information on the Internet. The process by which users filter information is frequently seen as a component of the consuming experience.

Table 3 shows how deep learning integrated it with CRM software for predicting intention. The gaps from previous studies were found in the variables used to support the consumption prediction based on Deep learning algorithms. The accuracy is different based on the techniques used.

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Table 3. An algorithm employed to predict consumers' intention to purchase.

#	Ref. & Publication Year	Techniques used in CRM prediction	Area of CRM	Data Source	Results	Accuracy
1	(Chen *et al.*, 2022)	Extreme boosting machine	Websites	Large European Ecommerce business retailer	Browsing content entropy features	XGBoost: 91.19% Logistic Regression: 94.26% GBM: 58.54% AdaBoost: 94.50%
2	(Li *et al.*, 2022)	Sentimental analysis	restaurants	Yelp dataset: 300 restaurants in Las Vegas, Nevada	Deep learning showed sentimental positive values were more related to pictures than text	N/A
3	(Chatterjee *et al.*, 2021)	Performance of the churn prediction	Telecom company	Orange Telecom	The pre-processing phase of the experiment using Lasso and manual feature engineering processed one dimensional dataset CNN was applied	98.85%
4	(Zhang *et al.*, 2021)	To identify the customer who stays active in a bank or leave	Bank	Indonesia	Use SVM classification with Machine learning	80%
5	(Cenggoro *et al.*, 2021)	DNN	Telecome company	3,333 telecommunication customers	Using discriminative vectors can reveal two groups of churning customers (leave, retaine)	81%
6	(Guo *et al.*, 2020)	Extreme gradient boosting (XGBoost)	E-Commerce	Consumers' behaviour in e-commerce platform	XGBoost perform very well with mobile phones selling	N/A

** (N/A) denotes unavailable information; Based on the author's knowledge.*

4.3. Deep Learning Algorithms in CRM

Plenty of algorithms have been investigated with consumers' intention to purchase. For instance, using simulated generated data for 10 customers. The prediction was very high with "not to buy" and very low with "to buy"-see the **Table 2**. However, the sample was very small and generated using computer simulation, which limits the effectiveness of the algorithm. A stacking ensemble model that uses a Multi-Layer Perceptron for consumers' intention to purchase. The findings showed deep learning outperforms other machine learning methods. However, two studies, in particular, that Random Forest was better than other machine learning algorithms, yet has not reached 90%, which is similar to reference. Cao *et al.* (2021) used Deep learning and employed more sophisticated matrices-related to eye tracking, to predict consumer intention with apparel websites.

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4.4. Types of Deep Learning Algorithms Used

Deep learning has been rapidly developing based on the neural network algorithm (Behera *et al*., 2022; Kusrini *et al*., 2022). It includes several well-known techniques that have been around for a while, such as the recursive neural network (RvNN), recurrent neural network (RNN), convolutional neural network (CNN), and deep Boltzmann machine (DBM). A short explanation of the prevalent fundamental approaches and applications field (Kumar *et al*., 2019). There are several deep learning algorithms have been used in several applications up to the present. **Table 2** shows the characteristics of each type of algorithm. They found that the intention could be increased when more navigation items have been used and placed the navigation at the top and left of the index page. **Table 3** lists some algorithms employed by researchers to predict consumers' intention to purchase. An overview of the customer turnover problem is examined in this paper using a variety of machine learning approaches, including XGBoost, Gradient Boost, AdaBoost, ANN, Logistic Regression, and Random Forest. Additionally, the different deep learning methods used to anticipate the customer churn issue, such as Convolutional Neural Networks and stacked autoencoders, are analysed by comparing the models' levels of accuracy. Due to their inability to foresee which customers would leave at what moment, telecom businesses commonly experience high customer turnover. Therefore, making an effective churn prediction model is necessary to identify the consumers who will quit the services at the right moment. This is vital in the telecommunications sector to retain their valued customers and develop their customer relationship management. Given its fiercely competitive business climate, the banking sector emphasizes customer relationship management (CRM) just as much as any other customer-oriented industry. A bank needs to understand its customers and provide prompt, personalized service because the financial industry is a data-rich industry with access to a wealth of consumer information and records of banking behaviour (Huang *et al*., 2022). Successful CRM aims to increase the efficiency of customer connection by communicating with customers and providing helpful, individualized services. The best in this part are the uses of deep learning that have been seen in aiding banking CRM. It is noticed that decision tree, Random Forest, and XGBoost are the highest accuracy among machine learning algorithms. Moreover, it was noticed that balanced datasets are used (where the number of records with no purchase is much more than records with successful purchases) then the accuracy of predicting unsuccessful purchases is as high as in.

The third notice was that a group of machine learning methods is used at the same time to assess their accuracies, which means that researchers may have no presumptions regarding the most appropriate algorithms that fit the selected dataset. The fourth notice was that deep learning algorithms that built on the top of CNN or LSTM outperform CNN and LSTM.

5. RESULTS & DISCUSSION

The result section concludes papers that been found based on questions we built in the methodology section and keywords used to collect the most relevant articles. Section A explains the total number of articles collected and what type of information they have inside; Section B checks the features that most papers used for purchase intention. Finally, Section C focused on the algorithms and models used on each article and divided them into using Deep Learning or other methods. The studies in the domain of employing Deep Learning and Machine Learning for consumers' intention to purchase prediction have grown considerably in recent years, as it can be seen that 10% of the total papers studied used

Deep Learning with CRM application where their objective centred on purchasing intention and 19 % used Machine Learning methods. This demonstrates that this domain is receiving considerable attention in the academic field and business.

5.1. Methodological Design

The various methodological design applied in the selected studies has been investigated. Based on the analysis, only 7 out of 55 reviewed studies used deep learning techniques to predict consumers' purchase intention **(Figure 2)**, while the remining 48 studies used quantitative approach (5 studies) , Data mining approach (17 studies), and machine learning methods (7 studies). Out of the above- mentioned 48 studies, 17 papers were review papers. Almost all quantitative approach studies have used SEM or PLS-SEM for the analysis, while few studies used other techniques such as multiple regression, logistic regression, MANOVA, ANOVA, etc. Hence it is understood that more Deep Learning studies are required to take place in this domain for improving knowledge. Though Machine Learning methods have been used more than deep learning, they can introduce no improvement when quite large datasets have been used and a very large list of criteria is found in those datasets. Then, the future seems promising for Deep Learning methods due to their capabilities to handle large datasets and improve accuracy while incremental data is provided.

5.2. Theoretical Foundations

The theoretical foundations of many papers found in depicting consumer's intention to purchase mostly tends to measure the influence of product quality, price, attitude, etc. some studies including demographic in their prediction such as (Chakraborty & Paul, 2022; Kansra & Oberoi, 2022; Yilmaz & Kahveci, 2022) who used gender and age. Even Deep Learning studies such as (Liu *et al*., 2021) considered gender in their prediction model. Regarding features of the product and online website, factors such as personal privacy, risk in giving card details, and tangibility of the product have been described as factors that negatively/positively influence consumers' intention to purchase (Kansra & Oberoi, 2022).

Meanwhile, Lin *et al*. (2021) focused on product characteristics (nutritional content, natural content, and ecological wealth) and platform characteristics (information quality, system quality, and service quality); and empirically proved they are more significant than consumer characteristics. In terms of theories, many papers integrated several theories to predict consumer purchase intention, for instance, Pillai, *et al*. (2022) integrated the theory of planned behaviour, the theory of perceived risks, and the elaboration likelihood model.

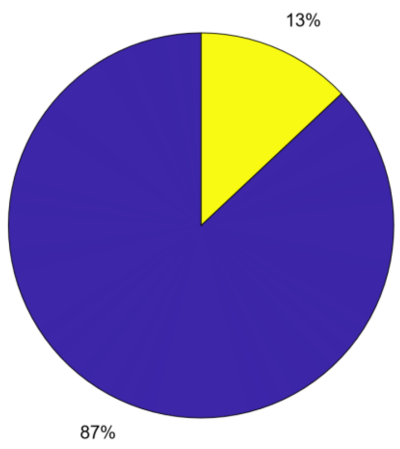

Figure 2. The percentage of studies used Deep learning to other studies.

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p- ISSN 2528-1410 e- ISSN 2527-8045

5.3. Thematic Foci

One of the themes was using an ensemble model, where many Machine Learning algorithms such as Decision Tree (DT), Random Forests (RF), Bagging, K-Nearest Neighbour (KNN), and Naive Bayes (NB) are tested altogether under similar conditions in order to determine the best performer. In many cases of this approach, the Decision Tree and AdaBoost were competing, and the Decision Tree was winning in many cases. **Figures 3** and **4** show the various themes found in the collected papers. For instance, in terms of the datasets used with Machine Learning methods and Deep Learning, historical data (clicks, visited pages, time spent on the website, browsed products, etc.), demographic data (age, gender, etc.), or instant behaviour. However, instant behaviour was used with Deep Learning only. The themes found in methods were testing single method, hybrid, ensemble, or models on the top of LSTM and CNN. So far, the studies that used Machine Learning are many, if compared to Deep Learning.

Overall, plenty number of algorithms and approaches have been found to predict consumers' purchase intention. During various experiment settings, they showed different accuracies. We have calculated the average accuracies of the major algorithms used and represented them in **Figure 5**. It seems that Logistic Regression (LR) method has high accuracy but, this is not reflecting the truth in result. Logistic Regression was only found in very few studies (two papers) and scored high with a limited dataset (records that were less than 5000). Meanwhile, the major papers found to combine several models (CNN, GRU, LSTM, PSO-XGBoost, etc.) to have more accurate predictions. The interesting fact about those combined models is their ability to sustain the same accuracy or improved when more data is included in the training.

The results in **Table 4** performed the better evaluation and compared between Deep learning models that show CNN and LSTM as successful techniques for purchase prediction including features such as purchase under number view products, sessions, and others. The support the investigation of deep learning models and pick up the most data entry findings process that could change results for prediction. Finally, many studies considered segmentation in order to have an effective prediction. It was noticed that researchers that worked on segmentations had contradictive views regarding the accuracy and effectiveness of segmentation.

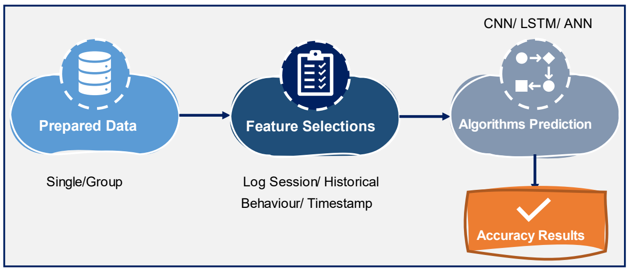

Figure 3. Data themes among studies reviewed in this study.

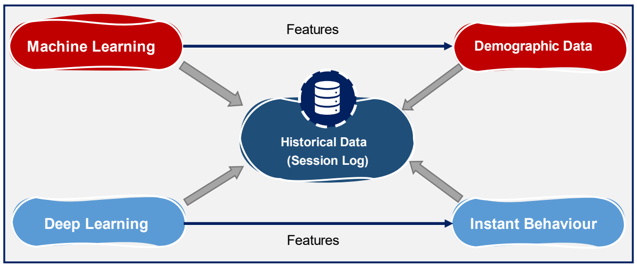

Figure 4. Models' themes among studies reviewed.

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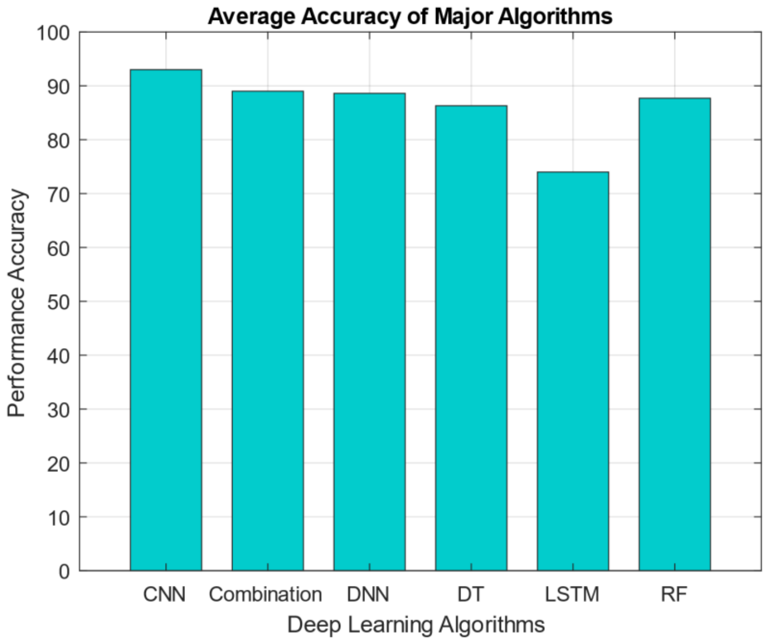

Figure 5. The average accuracy of major algorithms found predicting consumers' intention to purchase.

Table 4. Articles focus on deep learning beads on prediction consumption CRM.

#	Ref. & Publication Year	Algorithm	Data entry process	Industry/ Application areas	Features	Contributions	Limitations
1	(Chatterjee *et al.*, 2021)	CNN	Segmentation	Telecom company	Redundant data, Lasso, and manual feature engineering	CNN gives impressive results in detecting users, with 98.85%	More focus on network complexity and feature selection like Ensemble techniques
2	(Guo *et al.*, 2020)	ANNs, NNs, LSTMs, and GRUs	Segmentation	Banks (80 million credit card transactions)	Prevailing fraud detection methods such as Gradient Boosted Trees and Logistic Regression.	LSTM and GRU outperformed where ANN indicates useful information	improving network size increases and assessing model sensitivity to hyperparameters such as momentum, batch size.
3	(Schetgen *et al.*, 2021)	DNN	Segmentation	Online Business and Financial Services (EC)	Filter-based and wrapper-based	Improving prediction for e-commerce sales	Focus on retail sales, customer behavior in a particular product, and findings might not be generalizable across different product types.
4	(Kumar *et al.*, 2019)	Review Deep learning algorithms	N/A	Bank	Deep learning algorithm in Bank	Comprehensive review	More potentials need to be exploited
5	(Migdadi, 2021)	Adoption intentions	Segmentation	Social media (iPhone7 tweets and Xbox tweets)	CNN LSTM CNN-GRU CNN-LSTM MV-CLSTM	Proposes a novel analytical method that is better than other DL approaches.	To design a semi-supervised learning-based method for intention detection

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5.4. Discussion

The section discusses the algorithms found in the literature and the features used to calculate the predication consumption intention for CRM. In addition, the approaches from DL and ML and how using different criteria will affect the consumer's purchase intention accuracy. It can be noticed that simple Machine Learning models that are based on Random Forest or Decision Trees are good enough to recognize the oscillation and drifts in the market data. Then, they are cheaper alternatives for small companies. However, in general, Deep Learning and Neural Network outperform Machine Learning methods due to their ability to find patterns in complex features and handle considerable large datasets.

Regarding feature selection, practically, features could be hundreds and data is incomplete, therefore, many approaches have been followed to reduce the dimensionality and surpass empty cells. A Deep Learning model that successfully predicted 98% of consumers' intention to purchase. Evidence shows that Deep Learning has competitiveness over Machine Learning in some specific business tasks, particularly predicting consumer's purchase tendency, which is a significant issue in online business.

Then selecting input features is essential when using Machine Learning algorithms, although Neural Networks and Deep Learning are not affected by this because they can scan and choose the significant the features in an unsupervised manner. Therefore, machine learning methods are in need for careful selection of features before passing them to machine learning in order to reduce the computation power required and memory space. However; this is not the case with deep learning.

The challenge as well discussed is the ability to predict potential consumers while their online session is still active this is known as Early Purchase Prediction, this will bring benefit to consumers to get an instant discount or any rewards; and this challenge is discussed in (Esmeli *et al*., 2021). Usually using AI methods for future planning and not instant actions. However; this has changed as deep learning now can make an instant decision (e.g., autonomous car).

Then, this might be the future challenge for purchase intention prediction instantly. This LR study has found a lack of studies that employ Deep Learning to predict consumers' purchase intention. However, Machine Learning methods were many and performed excellently.

The possible challenge is that Machine Learning methods could not contribute well when very complex datasets are used with several issues in terms of missing data and dimensionality. Moreover; there is no specific feature set has been precisely determined by studies that adopted machine learning methods, though they used data collected from a web browser, which contains hundreds of features. The need to determine a specific short list of features is necessary to reduce the memory usage and computation required.

Prediction criteria related to consumer/visitor online activities are dominating other criteria and seems to continue in the future due to the following facts: (1) it is easy to be collected- online business can collect them while visitors surf the website; (2) a huge amount of data can be collected easily in a short period - when thousands of people visit the online business an endless number of clicks could occur, a large number of pages could be surfed, an endless list of products could be viewed and thousands of minutes could be spent within the business of the website; (3) these data can be easily retrieved and processed instantly by data analytics tools integrated with online business; and (4) they are the most direct data to consumer's purchase intention as they were collected while potential buyers surfing the website.

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6. CONCLUSION

It can be concluded that consumer relationship management is considerably focused on people's posts on social media because people reveal a lot regarding their perspectives towards products and purchase habits. Accordingly, prediction techniques such as Data Mining, Machine Learning, and Deep Learning have been utilized to predict purchase intention from people's online words and activities. However, compared to Machine Learning methods, Deep Learning methods are found to be underrated in predicting consumers' intention to purchase. This could be interpreted as follows: Machine Learning methods have been established in the field a long time ago, while Deep Learning is recently employed. However, Deep Learning is proceeding significantly in many fields including business, and replacing Machine Learning methods due to its capability to improve accuracy while more training data is included, to process complicated and high dimensionality datasets and need less human intervention.

Moreover, this research studied and compared the existing Deep Learning models that predict consumption and concluded that CNN and LSTM as successful techniques for purchase prediction, as CNN separately yields the highest accuracy of 90% and above. Additionally, the review highlighted that features such as purchase under number view products, sessions, and others, are among the prominent factors. The findings support the current investigation of using Deep Learning models and picking up the most used data entry process such as segmentation that could improve the results for prediction.

The future work concerns using deep learning, the combined architecture (CNN+LSTM) as it was proven in different domains their effectiveness, to develop purchase intention prediction with a very specific and short list of features. The challenge is to come up with a faster model with less memory space and high accuracy.

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8. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. The authors confirmed that the paper was free of plagiarism.

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