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A Systematic Review on the usage of Deep Learning Techniques in the Marketing Process

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This Dissertation was prepared in the context of the studies for obtaining a master's degree at the University of the Peloponnese and was approved by the members of the Examining Committee.

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DEDICATIONS

To my father, who is no longer among us, yet always present.

To my mother, who continued his support and was always there when I needed her.

To my loving husband–my rock, my friend–who gives me strength when I need it most and is always by my side.

and,

To my little daughter, who could not understand why I spent so many hours away, but whose jokes and smile remind me of what truly matters.

Thank you.

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ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
B2B	Business to Business
BERT	Bidirectional Encoder Representations from Transformers
BFM	Big Five Model
BI	Behavioural Intention
BiLSTM	Bidirectional Long Short-Term Memory
BPNN	Back Propagation Neural Network
CAD	Computer Aided Design
CNN	Convolutional Neural Network
CLV	Customer Life Value
CR	Conversion Rate
CTR	Click-Through Rate
DL	Deep Learning
DNN	Deep Neural Network
DCNN	Deep Convolutional Neural Network
DCNNP	Deep Convolutional Neural Network with Pooling
DSP	Demand Side Platform
DTCN	Dilated Temporal Convolutional Neural Network

FL	Federated Learning
GAN	Generative Adversarial Network
GRU	Gated Recurrent Unit
IDSS	Intelligent Decision Support System
LSTM	Long Short-Term Memory (a type of RNN)
ML	Machine Learning
MLP	Multi-Layer Perceptron
MMP	Mixed Marketing Plan
MPM	Mobile Performance Marketing
MPNet	Motion Planning Network
NLP	Natural Language Processing
PGM	Probabilistic Graphical Model
POI	Point of Interest
R&D	Research and Development
RL	Reinfocement Learning
RNN	Recurrent Neural Network
SL	Shallow Learning
STGCAN	Spatio-Temporal Graph Convolutional Attention Network
TSR	Total Shareholder Return
UI	Uset Intention

VAE	Variational AutoEncoder
VGG	Visual Geometry Group model
VR	Virtual Reality
XAI	eXplanable Artificial Intelligence

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Thank you.

ABSTRACT

This study aims to present a systematic review of research articles published between 2021 and 2024, found from the Google Scholar repository, and focusing on the application of deep learning (DL) algorithms in marketing. Two key research questions were examined: The first one identifies marketing activities and tactics within Kotler's Marketing Process that have adopted deep learning solutions, while the second one explores the specific deep learning implementations employed for marketing purposes.

Findings highlight the growing integration of deep learning across all steps of the marketing process, particularly in customer behaviour analysis, for the purpose of optimising promotion strategies. The field has moved from the use of basic deep learning implementations to the application of advanced, multi-layered deep learning systems that can support more dynamic, data-driven and personalized marketing approaches. Increasingly, hybrid models of CNNs, RNNs, LSTMs, Transformers and GANs are being used in real-world applications to analyse large-scale data and support real-time decision making, as well as to improve customer engagement.

As for the future work, the search methodology should be refined further to incorporate more specialized keywords to expand the search and include a wider range of relevant studies, and thus, to further identify emerging trends and critical research gaps in the evolving landscape of deep learning enhanced marketing.

Περιληψη

Αυτή η μελέτη στοχεύει να παρουσιάσει μια συστηματική ανασκόπηση ερευνητικών άρθρων που δημοσιεύθηκαν μεταξύ 2021 και 2024, τα οποία βρέθηκαν από το αποθετήριο του Μελετητή Google και εστιάζουν στην εφαρμογή αλγορίθμων βαθιάς μάθησης (DL) στο μάρκετινγκ. Εξετάστηκαν δύο βασικά ερευνητικά ερωτήματα: Το πρώτο προσδιορίζει τις δραστηριότητες και τις τακτικές μάρκετινγκ στο πλαίσιο της διαδικασίας μάρκετινγκ του Kotler που έχουν υιοθετήσει λύσεις βαθιάς μάθησης, ενώ το δεύτερο διερευνά τις συγκεκριμένες εφαρμογές βαθιάς μάθησης που χρησιμοποιούνται για σκοπούς μάρκετινγκ.

Τα ευρήματα υπογραμμίζουν την αυξανόμενη ενσωμάτωση της βαθιάς μάθησης σε όλα τα στάδια της διαδικασίας μάρκετινγκ, ιδιαίτερα στην ανάλυση της συμπεριφοράς των πελατών, με σκοπό τη βελτιστοποίηση των στρατηγικών προώθησης. Η έρευνα υποδεικνύει μια σημαντική μετατόπιση από τη αξιοποίηση βασικών εφαρμογών βαθιάς μάθησης στην εφαρμογή προηγμένων και πολυεπίπεδων συστημάτων βαθιάς μάθησης που μπορούν να υποστηρίξουν πιο δυναμικές, βασισμένες σε δεδομένα και εξατομικευμένες προσεγγίσεις μάρκετινγκ. Όλο και περισσότερο, υβριδικά μοντέλα CNNs, RNNs, LSTMs, Transformers και GANs χρησιμοποιούνται σε πραγματικές εφαρμογές για την ανάλυση δεδομένων μεγάλης κλίμακας και την υποστήριξη της λήψης αποφάσεων σε πραγματικό χρόνο, καθώς και για τη βελτίωση της αφοσίωσης των πελατών.

Όσον αφορά τις μελλοντικές εργασίες, η μεθοδολογία αναζήτησης θα πρέπει να βελτιωθεί περαιτέρω ώστε να ενσωματώσει πιο εξειδικευμένες λέξεις-κλειδιά για να επεκτείνει την αναζήτηση και να συμπεριλάβει ένα ευρύτερο φάσμα σχετικών μελετών και, ως εκ τούτου, να εντοπίσει περαιτέρω τις αναδυόμενες τάσεις και τα κρίσιμα ερευνητικά κενά στο εξελισσόμενο τοπίο του μάρκετινγκ με την εφαρμογή τεχνικών βαθιάς μάθησης.

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Chapter 1: Introduction

The digital economy is now a main driver of the growing global economy with digitalization becoming the main catalyst for change. This shift reveals the immense influence of the digital economy on different industries and thus points to a shift towards a new economic system. While more and more companies around the globe are digitizing their businesses, all the existing industries from manufacturing and services to education and healthcare are experiencing unprecedented changes that demand innovative and efficient solutions (X. Wang, 2024).

This transformation is a pivotal enabler, so is the integration of emerging technologies like cloud computing and artificial intelligence (AI). They not only improve operational efficiency but also redefine consumer experience as a central point for economic growth. But their adoption comes with challenges, most profound of them being security and privacy of information (X. Wang, 2024). In this landscape, marketing is going through a major change. The traditional marketing models are failing due to the digitalization of consumer behaviour and increased penetration of the Internet. Therefore, companies need to develop smart and data-oriented strategies to survive in this dynamic world.

The main problem that is facing the new digital environment is the growing need for digital marketing skills. Organizations need experts who can help in digital promotion, new media operations, e-commerce, and data analysis to navigate the current market environment. Nevertheless, despite the need for skilled workers, there is a significant gap between the available supply and demand. By 2025, this gap is expected to rise to about 40 million (X. Wang, 2024), which is a major issue for companies wanting to use digital marketing to achieve business growth.

Against this background, deep learning is an effective way to solve marketing problems, and can provide greater precision, prediction, and customer understanding. Thus,

solving the issues of data complexity and skill deficiency, companies can apply deep learning to improve marketing strategies, increase return on investment and build strong customer relationships (Eyvazli, 2023).

This study aims to investigate the transformative impact of deep learning on digital marketing. In this research work, the author aims to explore how the integration of deep learning techniques can help address the marketing talent gap, improve marketing efficiency, and lead to sustainable digital business growth. Hence, the present study will answer the following research questions:

RQ1: Which activities/tactics in the marketing process benefit from the application/usage of deep learning techniques, tools or products?

RQ2: Which deep learning techniques, algorithms or methodologies have been employed so far, to aid marketing process activities?

In the following chapters, the basic concepts of the marketing process and deep learning algorithms are highlighted in Chapter 2: Key Concepts. Then, in Chapter 3: Methodology, an analysis of the systematic review followed in this study is presented. In Chapter 4: Related Work, an analysis of similar research studies is provided and the contribution of this study to research is identified. The results of RQ1 and RQ2, are provided in Chapter 5: Marketing Activities/Tactics Exploiting Deep Learning Implementations and Chapter 6: Deep Learning Techniques/ Algorithms/ Methodologies employed in Marketing respectively, followed by the Discussion of the results and the Conclusion of the study.

Chapter 2: Key Concepts

2.1 Marketing

(Kotler et al., 2020) define marketing as a process that consists of five steps that create value for the customers and develop relationships with the customers, with the aim to lead to value, captured from the customers. The first step in this process is to understand the marketplace and the customer's needs and wants. The second step is based on the findings of the first and results in the design of a customer value-driven marketing strategy. During the third step, and based on the selected strategy, an integrated marketing program is constructed to deliver superior value. The fourth step is to engage customers and create beneficial relationships that would lead to customer delight. In the last step companies derive value from customers and generate profits and customer equity.

Figure 1: The Marketing process as defined by (Kotler et al., 2020), Source: Principles of Marketing (pp. 154)

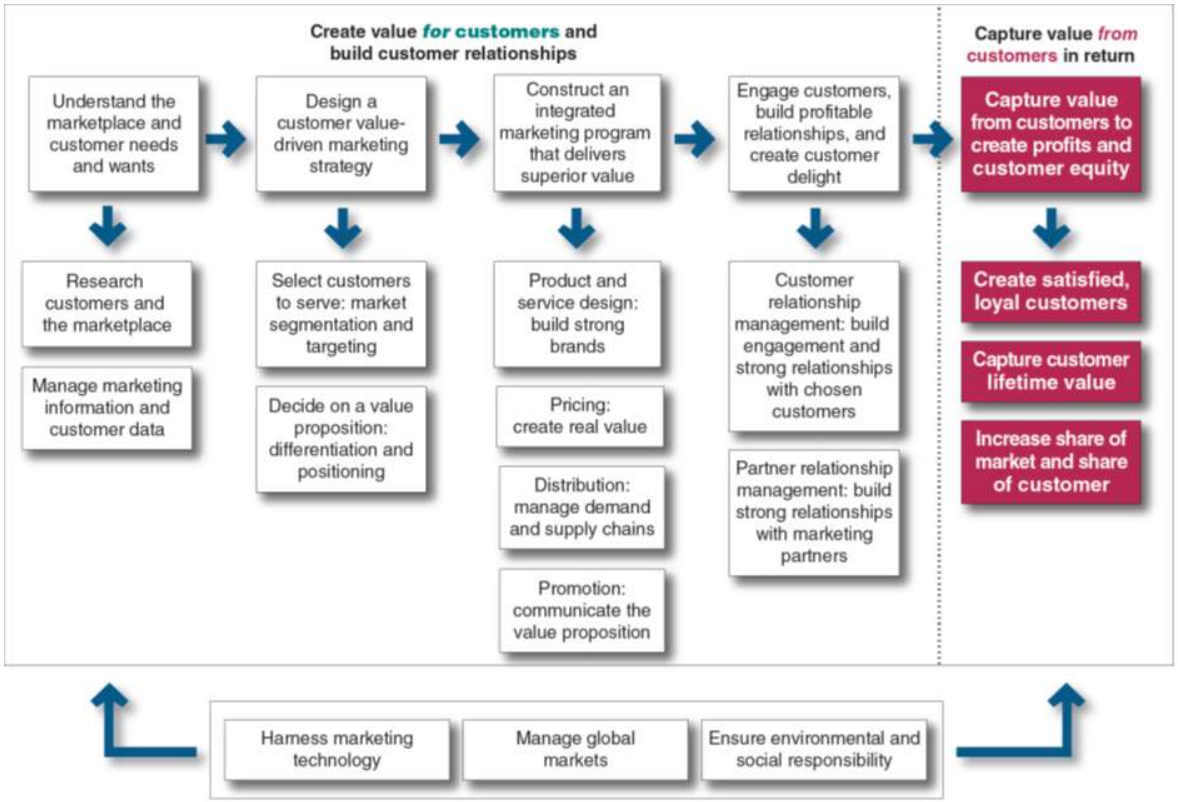

Figure 1: The Marketing process as defined by (Kotler et al., 2020), Source: Principles of Marketing (pp. 154)

The people who are responsible for each of the activities and tactics in each step, are not isolated from the rest of the process. Instead, they provide their assessments and results to the people in charge of other steps of the process, thus becoming useful for further research, rescheduling, reconfiguration, and tuning of the activities and tactics performed. As described, it is a time-based process. In this work, our analysis of marketing activities and tactics is provided through the five-step process. The findings of our study in relation to the first research question are presented in the context of the marketing process steps.

2.2. Deep Learning

Deep learning is a subfield of artificial intelligence that is concerned with developing very large neural network models that can make near optimal data-driven decisions. It is particularly useful in complex data settings and when there are large amounts of data available. Deep learning has its origin in AI and ML research, and one of the primary objectives is to design a system that can learn functions that map inputs to outputs (Kelleher, 2019). Functions can be described in different ways and deep learning uses deep neural networks to learn patterns from data and encode the learned function in the networks. That is why deep learning is such a vital tool in current marketing, where it is crucial to recognize and forecast consumer behaviour from big data in order to make the right decisions.

In Table 1: Main Deep Learning Algorithms, a list of the main algorithms used in deep learning is presented, and along with each algorithm its key purpose, main application, strengths and weaknesses are described, as identified by several researchers.

Table 1: Main Deep Learning Algorithms

Main Algorithm	Supervised/ unsupervised	Purpose	Applications	Strengths	Weaknesses
Convolutional Neural Networks (CNNs) (LeCun, 2015)	Supervised	Image processing and feature extraction	Computer vision, medical imaging, facial recognition	Excellent for spatial data, automatic feature extraction	Requires large datasets and computational power
Recurrent Neural Networks (RNNs) (Lipton et al., 2015)	Supervised	Sequence data processing	Speech recognition, language modeling, time-series forecasting	Captures temporal dependencies, effective for sequential data	Prone to vanishing gradient problem
Long Short-Term Memory (LSTM) (Hochreiter & Schmidhuber, 1997)	Supervised	Long-range sequence modeling	Machine translation, text generation, speech synthesis	Addresses vanishing gradient problem, better memory retention	Computationally expensive
Transformer Networks (Vaswani et al., 2017)	Supervised	Sequence-to-sequence modeling	Natural language processing, machine translation	Handles long-range dependencies efficiently	Requires extensive training data and computation
Autoencoders (Hinton & Salakhutdinov, 2006)	Unsupervised	Unsupervised feature learning	Anomaly detection, data compression, denoising	Learns compact representations, effective for dimensionality reduction	Poor generalization for complex tasks
Generative Adversarial Networks (GANs) (Goodfellow et al., 2014)	Unsupervised	Generative modeling	Image synthesis, style transfer, data augmentation	Generates realistic data, used in creative applications	Training instability, mode collapse

Chapter 3: Methodology

To conduct our systematic review on research articles referring to the way deep learning is used for marketing purposes, we used the PRISMA guidelines (Page et al., 2021). The research was conducted from July 2024 to November 2024 on the Google Scholar database, for articles published between 2021 and 2024 (last four years), as our focus is on how recent developments in the field of Artificial Intelligence and more specifically Deep Learning, have affected different aspects of the marketing process.

For the research questions described in Chapter 1: Introduction, we used the search terms “deep learning”/ “marketing”, combining the first term (deep learning) with the second term (marketing) using an “AND” operator. Both research terms should be found in the title of the research articles.

The initial search resulted in 97 outcomes, of which 4 (2 couples) were duplicates, and 7 were not relevant. Our work focuses on the period after 2021, thus excluding 19 outcomes and resulting in 69, of which 4 were articles in scientific journals, that were retracted due to various scientific reasons (review process, use of data etc.), 8 were not accessible, thus resulting in 57 outcomes to proceed further in their assessment against the following eligibility criteria:

Inclusion criteria:

IC1. Article related to both search terms specified above.

IC2. Article related to at least one of the research questions.

Exclusion criteria

EC1. Article that is not written in English

EC2. Article in the form of a one- or two-page abstract, lesson, or poster

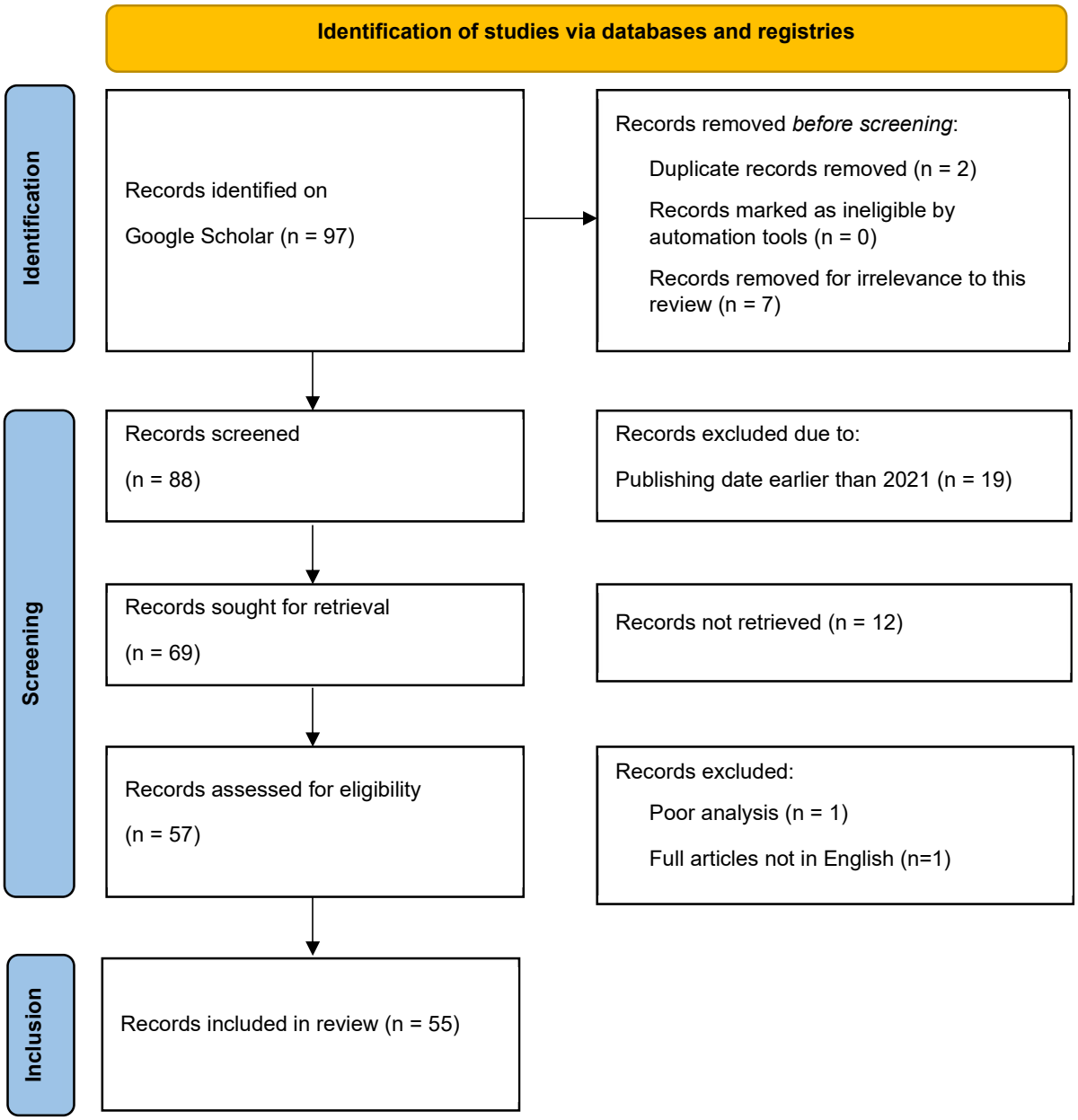

Figure 2: Selection of articles according to the PRISMA methodology for conducting systematic reviews

After the exclusion of 1 research study that was not written in English, and 1 that was not clear if the described algorithms were deep learning implementations or machine learning implementations, the final list consists of 55 articles. Of them, 6 articles are review articles which are presented in Chapter 4: Related Work, to form the bases of this research study. Apart from the 6 review articles published after 2021, 2 more review studies from previous years were included as they provided valuable information for our research.

The majority of the remaining articles corresponds to both RQ1 and RQ2 (43), however 3 correspond only to RQ1, as no details are provided for the deep learning algorithms used in the context of their study and, 3 correspond only to RQ2 as they focus on algorithmic details and provide no further analysis on their application to specific marketing activities.

Chapter 4: Related Work

Before 2020, only about 20 research articles used the terms ‘deep learning’ and ‘marketing’ in their title. In 2020, the first review paper that contains both terms in the title of a scientific article is published (Mehta & Mehta, 2020) and the focus is given to the application of Artificial Intelligence in the development of marketing strategies, production scheduling, strategic decision making and customer value prediction. Nevertheless, the articles studied in the referring work do not use the term deep learning in their description. The authors focus on different aspects of AI technologies such as artificial neural networks, fuzzy logic, decision support systems, and multi-agent systems. One of the scientific articles (S. Li, 2000) is exceptional in that it discusses the design of a neural network combined with fuzzy logic and decision support systems to assist marketing managers in the formulation of marketing strategies especially in the light of uncertainty in this marketing process.

Since then, just over a handful of review papers are relevant to the application of deep learning techniques, algorithms and frameworks in the marketing process, as defined in (Kotler et al., 2020), and most of them are published during 2023 and 2024, indicating that today, DL techniques are rapidly gaining the attention of the marketers.

In (Liu, 2023), the author examined research articles from leading marketing journals. The reviewed articles were identified from the listed journals, through a search using the keywords “DL” and “deep neural networks (DNN)”. The overall objective of the study was to investigate the use of DL in marketing. In doing so, the study offers a clear and concise explanation of the basic theory of DL, the algorithms and the main technical issues that affect the implementation and efficacy of the models and the resulting output. Through the reviewed articles, the study explains the implementation of six popular deep learning algorithms (CNNs, RNNs and LSTMs, Transformers, VAEs, GANs, RLs) and how they can be useful in solving different marketing problems that involve unstructured data. It was found that DL is most

effective and versatile in dealing with unstructured data like product design, customer needs analysis, promotion, targeting, and demand forecasting. The author argues that DL can greatly enlarge the research frontiers of marketing by allowing the evaluation and management of unstructured marketing data that are currently hard to measure and manage. The work suggests using DL either as: i) a generic, out of the shelf solution, ii) a configurable solution which combines (ii-a) stuctured and unstructured data, (ii-b) DL architectures which are driven from or initialized by supporting 'marketing' theories, or (ii-c) constraints from the marketer's practical experience. The author suggests that future research should focus on enhancing the efficiency of the models, integrating multimodal data and using DL for causal inference and reinforcement learning in the marketing context.

In another interesting research (Prabadevi et al., 2022), the authors present a high-level overview of DL and its applications in the marketing field. The scientific articles included in the research were chosen through a systematic literature review and quantitative techniques such as bibliographic coupling. The authors focus on identifying how marketing researchers can utilize DL, based on the application of DL solutions described in key marketing and management journals. However, there is no information on the actual methodology or the selection procedure in the work. The study found that 412 distinct types of theoretical "lenses" were identified, but they do not state how many papers were found, and they do not provide further details on the different theoretical lenses, as they are mentioned in their work. Similarly to (Liu, 2023), the authors note that the use of DL has the potential to significantly improve marketing strategies, especially when combined with explanations. They also stress the importance of predictions made from multiple sources of information and report increasing scientific interest in these issues in the literature. The authors argue that more research should be conducted on the cross-fertilization of ideas across disciplines and focus on areas that have not been adequately explored to fully exploit the potential of DL in marketing.

Some other review articles focus on particular aspects of the marketing process, or on particular tactics within the marketing process, such as on interactive marketing (Yu, 2023), engagement marketing (Yu & Liu, 2024) and adaptive content recommendation systems (Muniandi et al., 2024) or on particular industries, e.g. Communication Marketing for the Film Industry (P. Yang, 2024).

In (Yu & Liu, 2024), the authors sampled 656 articles from peer-reviewed journals which were sourced from the Scopus database. Articles were identified for inclusion in the study using search terms from the concepts of engagement marketing and deep learning. They applied bibliometric analysis and for this purpose, employed tools such as SciMAT to analyze trends and the impact of the scholarly publications. The authors aimed to investigate the role of deep learning in engagement marketing, specifically in the context of interactive marketing. The main findings identified several trends in the application of deep learning, including language interaction, interactivity-privacy, and human satisfaction. Another significant finding is how the use of various terms shifted across the literature from the pre-2015 period up to 2024. The development of key research topics was tracked down through several thematic areas: Linguistics developed to decision making information management, customer engagement, and finally, chatbot and commerce. Algorithms shifted through crowdsourcing, performance optimization, recommendation systems, and social media marketing. Moreover, interactive marketing methodologies shifted to address personal data privacy concerns. The authors recommend that future work should aim for the integration of AI into human-centred frameworks, to solve newly appearing issues, such as negative customers' experiences and unfair treatment, and to implement multimodal deep learning frameworks to gain a better understanding of consumers' behaviour.

Furthermore, in (Yu, 2023), the author explores how the adoption of DL has changed the way of implementing interactive marketing activities. In this paper, the author chose several

scientific articles from various areas, including marketing, computing and statistics. It is a valuable source of information that can help to understand the theoretical foundations and the practical applications of DL in the marketing process. It gives a deep insight of the DL algorithms for predictive modelling in customer identification, growth and retention. It also examines the application of DL in increasing the customer participation through referral programs and feedback mechanisms. In the area of marketing communication, the research work explains how chatbots developed with the help of DL can assist in real-time interaction with the customers. In product innovation, it describes how DL can be employed to identify customers' wants and needs and create new products with the help of Generative Adversarial Networks (GANs). The study also looks at the application of DL techniques such as NLP in social media listening, customer sentiment analysis, and matching text to relevant images or memes developed with the help of GANs to increase user engagement.

Additionally, as in (Liu, 2023), the author also gives an overview of various DL algorithms and models such as FNN, CNN, RNN and its variants, i.e., LSTM and GRU, and finally, GANs. It highlights the training, tuning and transfer learning processes that are useful to assess the effectiveness of DL applications. The study highlights the use of pre-trained models (e.g., VGG, ResNet, BERT) to save resources, and the application of autoencoders for dimensionality reduction and feature selection. However, while highlighting the advances in DL and automation, the author argues that the role of human judgment cannot be overlooked in marketing and suggests that the relationship between marketers and data scientists will be crucial in the future. The work recognises the dynamics of future technology trends such as the Metaverse and wearable devices in conjunction with the application of DL based solutions for marketing.

In (Muniandi et al., 2024), the authors performed a comprehensive review of relevant literature and case studies from a collection of articles that focus on adaptive content

recommendation systems and deep learning techniques. These articles were collected from different journals, conferences and research papers, including seminal works. In this work, different aspects of recommendation systems were considered, including user-based, context-based, time-based, and content-based adaptations, and hybrid strategies that combine several of these techniques. DL algorithms and models, such as CNNs, RNNs and hybrid models were identified for their potential to learn complex relationships and trends in the data related to user behaviour and content features. The main findings show that the use of DL models enhances the accuracy and personalization of content recommendations significantly, which in turn increases user engagement and satisfaction. The authors recommend that future work should consider the integration of advances in multimodal data, the cold-start issue[1], and the understandability and deduction of the recommendation systems.

On a different research aspect, (P. Yang, 2024) investigates how DL models and algorithms are used in the marketing of the Film Industry. The study uses literature review and case study analysis. The articles were chosen for the study based on their relevance to the research status, trends in development, and problems, using search terms “Cinematography” and “Media Marketing” in combination with “CAD” technology and “deep learning”. The major conclusions are that DL tools and algorithms, including CNNs, are employed for the statistical analysis of audience data, preferences and behaviour patterns recognition to improve the visual and sound effects of movie trailers and film scheduling. The application of CAD technology enhances the generation of realistic 3D scenes and characters, thus enhancing the efficiency and quality of film production.

Almost all the reviews analysed so far (Yu, 2023, Muniandi et al., 2024; Yang, 2024; Yu & Liu, 2024), have emphasized the need for data protection and privacy and the need to address the issues of bias in deep learning algorithms. They also stress the importance of

[1] Initialling behaviour prediction for unknown users

integrating and using multimodal data in deep learning models. In (P. Yang, 2024), the author raises another concern, namely that the use of DL could result in the standardization of film content and thus limit creativity and new ideas.

On the other hand, there is only one review study which is aimed at purely technical issues of DL algorithms and their possibility to incorporate them into the marketing process. In (Mageed et al., 2024), the study focuses on the algorithms and models, and more precisely on the comparison between shallow learning (SL) and deep learning (DL) techniques. Although the work is illustrated using applications in specific domains like finance, marketing and e-commerce, the focus is on the performance of various machine learning models and algorithms in these areas. The discussion is based on the capabilities, advantages, and limitations of the SL and DL methods in performing complex tasks and extracting features from the data but not on the specific elements of the marketing process or the other research fields (finance, e-commerce). The first finding is that DL models are better at handling complex and nonlinear functions. The authors suggest that CNNs and LSTM algorithms are better than traditional SL methods in terms of accuracy and the ability to learn features directly from data. They also stress the need to continue researching to solve the problems of training DL models and to search for new applications across different fields.

Ultimately, the present work is a systematic literature review in line with the PRISMA guidelines (Page et al., 2021). The two main issues considered are: i) The activities in the marketing process (Kotler et al., 2020) which embraced the DL theory, pre-trained models and custom applications, and ii) The DL algorithms, techniques or tools that are most frequent in the literature for marketing purposes. In the end, we hope to determine issues that have not been addressed or the biggest obstacles as perceived by either technical or marketing experts. The most recent review articles (2024) are dedicated to particular aspects of the marketing process such as interactive marketing (Yu, 2023). They review the impact of implementing DL

solutions on customer engagement (Yu & Liu, 2024) and adaptive recommendation systems (Muniandi et al., 2024). One review article focuses on a particular industry (P. Yang, 2024) – film communication, and another one on DL algorithms that can be used in the marketing activities (Mageed et al., 2024). Nevertheless, through the literature review performed for this study, it was identified that DL solutions were also discussed in other steps and activities of the marketing process during the last 4 years. Thus, the aim of this study is to fill the gap and cover the lack of such review for any part of the marketing process, as the last general study was published in 2023 (X. Liu, 2023) and covered the literature up to 2022. A brief overview of related review articles and the contribution of the present study to the existing literature is provided in Table 2: Summary of Review Articles on Deep Learning and Marketing (Related Work).

Table 2: Summary of Review Articles on Deep Learning and Marketing (Related Work).

Authors	Title	Publication Date	Research Focus	Methodology	Sources	#papers included	Research Lifespan	Contribution	Comments
Mehta & Mehta, 2020	How Artificial Intelligence and Deep Learning led to a Breakthrough in Marketing and Consumer Behaviour: A Review.	**2020**	Application of **AI** in developing: • marketing strategies • production scheduling • strategic decision-making • customer value prediction	-	-	5	Up to 2020	Indicates the following Strengths: • Digital Audio Processing with AI, enabled Media Campaign Tracking • Enabled the development of new technologies such as intelligent machines, tools, robots and Challenges: • Inability to transfer knowledge from the expert user to the model	Focuses more on AI systems, rather than DL. Key articles selected span from 2002 to 2011.
Prabadevi et al., 2022	The Deep learning based service dominant environment for marketing management and customer services with secured Internet of Things	**2022**	• Provide a high-level overview of deep learning (DL) and its applications in marketing, consumer research, and psychological knowledge • Identify how marketing researchers can utilize DL	Systematic literature review Bibliographic Coupling	-	49*	2013-2022	Provides an overall guidance for implementing, evaluating and managing the usage of DL solutions in the marketing process. Continuous evaluation of DL solutions in marketing is suggested, as part of the marketing process.	Focus in on IoT technologies and how to manage technological changes effectively.
Liu, 2023	Deep Learning in Marketing: A Review and Research Agenda	**2023**	Explore the application of DL in marketing process	Systematic literature review Search terms "DL" and "Deep Neural Networks"	Journals: Marketing Science, Management Science, Journal of Marketing Research, Journal of Consumer Research, Journal of Marketing, Quantitative Marketing and Economics	19	up to 2022	DL is particularly powerful and flexible for modelling unstructured data, such as product design, customer needs identification, promotion targeting, and demand forecasting. It suggests marketers to use DL solutions as: Plug and Play, off-the-self tools or Customisable solutions based on combining multimodal data and marketing theory	Focus is on providing technical details and explaining how key DL methods and algorithms work, their advantages and key evaluation issues.
Yu, 2023	Deep Learning Applications for Interactive Marketing in the Contemporary Digital Age	**2023**	Critical resource to understand the theoretical underpinnings and practical implications of DL in the contemporary marketing landscape	Key articles in marketing, computer science and data analysis	Author's selection	103*	2015-2021	It suggests marketers to use: • Pre-trained models to save resources, and • Implement autoencoders for dimension reduction and feature extraction. It underlines the importance of human judgement and stresses the need for close collaboration of experienced marketers with data scientists.	Focus in on Interactive Marketing.

* Not explicitly mentioned, but estimated from the number of papers referenced in this work

Table 3: Summary of Review Articles on Deep Learning and Marketing (Related Work) - continued

Authors	Title	Publication Date	Research Focus	Methodology	Sources	#papers included	Research Lifespan	Contribution	Comments
Yu & Liu, 2024	Deep learning application for marketing engagement – its thematic evolution	**2024**	Examine the evolving role of deep learning in engagement marketing, particularly in the context of interactive marketing	Bibliometric Analysis	Peer Reviewed Articles from Scopus	656	up to 2024	Interprets how research keywords evolved in DL and Marketing during 5 periods defined from pre 2015 to the last one in 2023-2024.	Focus in on Engagement Marketing
Muniandi et al., 2024	Adaptive Content Recommendation Systems for Digital Marketing Platforms: A Deep Learning Approach	**2024**	Explores the role, in marketing, of adaptive recommendation systems, implemented with DL techniques	Literature Review and Case Study Analysis	Various academic journals, conference proceedings, and research papers, including seminal works (not explicitly named)	20*	up to 2019	DL models significantly enhance the accuracy and personalization of content recommendations, leading to higher user engagement and satisfaction	Focus is on Recommendation Systems
Yang, 2024	The Application of Deep Learning in Film Communication and Media Marketing	**2024**	Explores how DL tools are used in the Film Industry	Literature Review and Case Study Analysis Search Terms: "Deep Learning", "CAD", "film communication"	-	15	up to 2017	DL is used to analyse large amounts of audience data, predict preferences and behaviour patterns, enhance visual and sound effects in movie trailers, and optimize film scheduling strategies.	Focus is on CAD and film communication
Mageed et al., 2024	Shallow Learning vs. Deep Learning in Finance, Marketing, an e-Commerce	**2024**	To compare SL to DL solutions for finance, marketing and e-commerce	Key articles in marketing, information systems and engineering, neuroscience	Author's selection	18*	2016-2023	Superior performance of DL models in handling complex and nonlinear functions. The authors suggest that DL techniques (CNNs, LSTM), offer significant advantages over traditional SL methods, particularly in terms of accuracy and the ability to automatically extract features from data.	Focus is on the capabilities, advantages, and limitations of SL and DL methods in handling complex tasks and extracting features from data, rather than on specific elements of the marketing process
This study	**Deep Learning in the Marketing Process**	**Feb 2025**	**To identify how DL is used for marketing purposes**	**Systematic Literature Review (PRISMA) Search Terms "Deep learning", "Marketing"**	**Google Scholar**	**55**	**2021-2024**	**During the last 4 years, identify:** • **The activities and specific tasks in the marketing process that benefitted from the application of DL.** • **The most prominent deep learning techniques, algorithms or methodologies employed in the marketing process.**	**Focus is on both marketing and DL algorithms aspiring to provide a comprehensive analysis to both marketers and technical specialists.**

* Not explicitly mentioned, but estimated from the number of papers referenced in this work

Chapter 5: Marketing Activities/Tactics Exploiting Deep Learning Implementations

In this chapter, an overview of the results from the marketing perspective, as described in RQ1, is presented. Figure 3: #papers per Marketing Process Step and Main Step Activities, provides a synopsis of the five steps in the marketing process and the distribution of research studies across each step. As observed, most of the research between 2021 and 2024, focuses on Step 3 and Step 4, while Step 1 also accounts for a significant percentage of articles. However, some of the key activities within each step are still unexplored, which means that the interest in the marketing process is focused on certain topics. The remaining sections of this chapter will discuss these findings in detail.

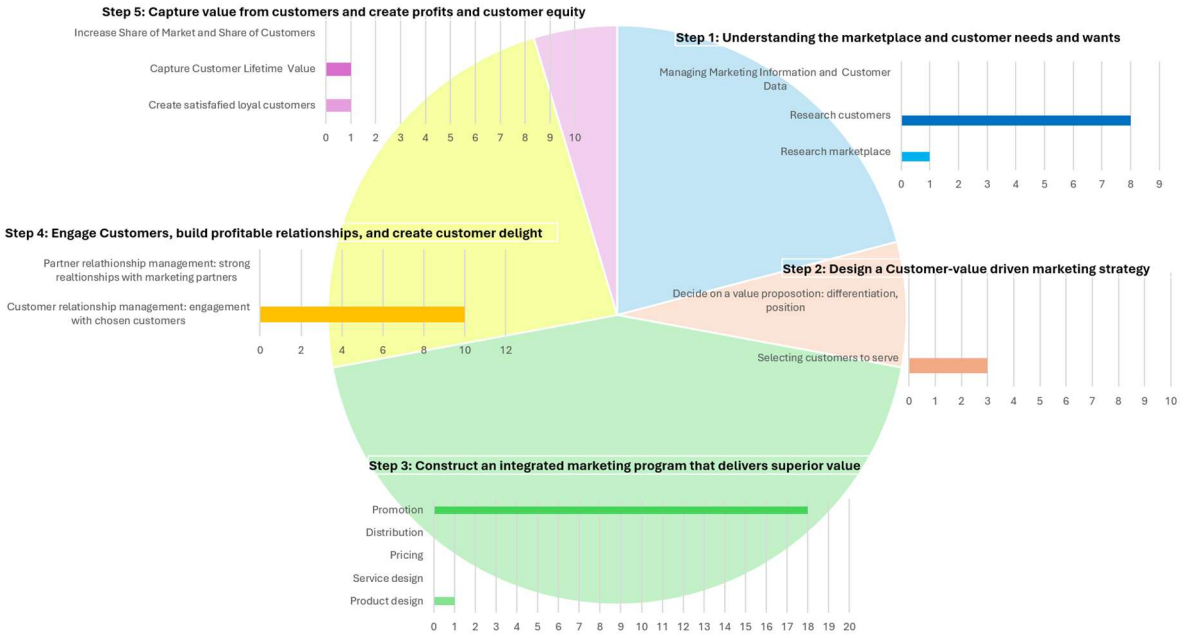

Figure 3: #papers per Marketing Process Step and Main Step Activities

5.1 Step 1: Understanding the marketplace and customer needs and wants

5.1.1. Research marketplace

Competitiveness evaluation

In (Zhang, 2023), the author points out that identifying the marketing competitiveness of B2B e-commerce companies is complicated due to the prevalent price wars, deceptive advertising, and unsustainable business models that are used strategically to capture market share quickly. It is claimed that traditional evaluation frameworks do not offer a full view of marketing competitiveness and therefore a more sophisticated approach is required. To this end, the study proposes a deep learning model based on Backpropagation Neural Network (BPNN) to support firms in identifying their market position. The model incorporates both subjective and objective evaluation criteria to assign dynamic weights to the key competitiveness indicators and calculate a single competitiveness score. Interestingly, **fixed asset turnover rate** is revealed as the most important factor in competitiveness, followed by **brand value** and the **R&D investment to total sales ratio**, which reiterates the significance of operational efficiency and innovation in the success of B2B e-commerce.

The proposed model is found to be substantially more accurate than the conventional valuation techniques such as relative valuation, discounted cash flow analysis, and absolute valuation models. However, the researchers acknowledge that the model was trained and validated using a relatively constrained dataset, hence the need for further empirical validation to determine the robustness and generalizability of the model across different market settings.

5.1.2 Research customers

Understanding customer behaviour

(X. Wang, 2024) provides a holistic view of how and where traditional enterprises should try to manage and integrate the marketing data to a greater extent in order to survive in

the market. The author notes that many traditional companies experience challenges in the management of marketing information and that currently available resources and approaches are not ideal for sorting and analysing the data.

The study also points out that organizations struggle to **precisely analyse users' behaviour and market trends** and, therefore, cannot develop effective market responses. The author is very much in agreement with the need for change in organizational approaches and strongly recommends that companies adopt data-driven decision-making systems and hire people who can help manage the data complexity. In addition to recommending the Digital Marketing Skills Model, a competency model that the author has proposed for identifying the competencies required for the adoption of deep learning techniques in marketing, the author also highlights the importance of deep learning algorithms in the management and analysis of large amounts of data to gain a better understanding of consumer behaviour and market trends. The research article supports the author's claims through empirical studies that showed how the adoption of DL techniques improves the overall value and competitive position of traditional enterprises.

In (Löwe, 2021), the author explores the fact that for AI solutions (including ML and DL) to become adopted in the marketing process, it means a change in the way that AI-generated strategies are perceived and used. Even though ML and DL hold the promise for enhancing the effectiveness of mixed marketing plans (MMPs), their black box decision making poses a problem for marketing professionals who cannot explain how the intelligence-based recommendations given are related to their own experience-based approaches. This thesis proposes a new strategy for increasing the level of transparency and building confidence to the deep-learning proposed decisions, by combining probabilistic graphical models (PGMs) with neural networks using approximation methods. This method is implemented through the use of rapid, iterative feedback loops between the DL model generated plans and the user,

which creates a collaborative human-AI interaction that not only accelerates the optimization process but also ensures that the recommendations are consistent with the marketers' cognitive frameworks. In the end, this approach improves the interpretability of AI so that data-driven marketing plans are easier to understand, act on, and embed in the real world strategic decision-making process.

Other works present more applicable findings, e.g., in (Yavuz, 2022) which aims at **identifying the characteristics of purchasing behaviour** and the perception and characteristics of service consumers. Using both supervised and unsupervised machine learning methods and advanced deep learning strategies, the study arrives at explorative and confirmative findings on consumer behaviour. A new classifier was proposed based on different features such as brand features, service features, and consumer-related features to develop a model that can help in the identification of the factors that influence purchase behaviour in the context of service marketing. The results show that purchase behaviour on the online channel is influenced by several variables related to the consumer and their preferences and profiles and that the proposed model offers a better understanding of consumer behaviour and better prediction accuracy than the conventional approaches.

In another study, contributing to customer behaviour understanding, (Labti et al., 2023) examine ways for effectively marketing the VR technology for shopping. They explore various factors, but mostly personality traits, that influence consumers' adoption intention. Given the uncertainty in human behaviour, the study uses an integrative approach, based on the Big Five Model (BFM) and introducing a new construct, the Perceived Enjoyment (PE) to explain the determinants of Behavioural Intention (BI) towards the adoption of VR shopping. The data were collected using an online survey and 399 postgraduate and graduate students in Morocco and were analysed using advanced computational methods including a DL algorithm (Multilayer Perceptron). The results show that **Openness to Experience, Extraversion,**

Agreeableness and Perceived Enjoyment all have a significant and positive effect on the intention to adopt VR shopping. Neuroticism had a significant negative effect while Conscientiousness had no clear impact. The artificial neural network (ANN) analysis also revealed that Openness to Experience and Extraversion were the most important predictors of VR shopping adoption. These insights shed light on the effectiveness of deep learning tools in identifying unique trends in consumer behaviour and developing specific marketing plans.

In the changing world of social media marketing, another research article explores how to understand the specific role of both textual and visual elements as they are key for user engagement. (L. Liu et al., 2021) is the first to propose a deep learning-based approach to measuring text image congruency in terms of relevancy and expectancy using the Weibo[2] data set. The results are quite interesting: **only both extreme congruent (high relevancy, high expectancy) and incongruent content (low relevancy, low expectancy) affect user engagement**, and the effect is different for shares and comments. Conventional wisdom so far, recognises that only harmonious integration of text and image increases user engagement, but the results in this study indicate that deliberate incongruity could act as a dynamic marketing tactic. The study provides a scalable methodological framework for analysing large amount of social media data, which can help marketers develop practical recommendations for creating more effective content strategies in the digital marketing environment.

Understanding customer sentiments

Both (Almutairi & Alotaibi, 2023) and (Nouri et al., 2023) consider the use of sentiment analysis in Arabic reviews with the goal of identifying consumer sentiments and improve the quality of products and services. Both studies use deep learning strategies and ensemble learning. The model development is the main focus of (Almutairi & Alotaibi, 2023) and the

[2] Chinese microblogging website (social media).

authors stress the necessity of using a large corpus of data for successful sentiment analysis; nevertheless, (Nouri et al., 2023) prove that their proposed ensemble model is better than individual models, included in it, in terms of accuracy and overall performance, thus recommending this approach for the analysis of sentiments in Arabic texts.

(Arafat et al., 2021) analyses the content on a more specific level and uses deep learning to identify the emotional state in the advertisements. The authors argue that the growing inefficacy of the advertisements is due to the exclusion of emotional intelligence in the audio and video campaigns. At the same time, brands spend much time on the description of the features of the product, but they do not pay attention to the emotional aspects that influence the consumer's choice and engagement. This paper contributes to the literature by developing a framework for applying deep learning to **identify and analyse the emotional dimensions of arousal, valence, and dominance in advertisements**, in order to predict their effect on purchase intent and audience reaction. Through these insights, marketers can create emotionally powerful campaigns that not only grab the attention of the audience, but also enhance brand loyalty and conversion, and, therefore, change the current trends in digital advertising.

5.2. Step 2: Design a customer-value driven marketing strategy

5.2.1 Selecting Customers to serve related activities

Performing Market Segmentation and Targeting

Over the past few years, researchers have progressed significantly in customer segmentation via novel approaches. (C. Wang, 2022) suggested a customer segmentation model based on selected features and used a Deep Neural Network (SONN) to classify clusters into five predefined categories. This model proved to be highly effective with an accuracy of 98.67%, which is higher than other DL methods. (Talaat et al., 2023) proposed a solution to the

problem of interpretability, presenting the DeepLimeSeg model that combines deep learning and explainable AI (XAI) approaches. Using demographic data, behavioural patterns and purchase history, they were able to develop effective marketing strategies. In an analogous way, (Benbrahim Ansari, 2021) presented a new approach for the B2B industrial automation sector using Self-Organizing Maps (SOMs) for the analysis of geo-referenced high-dimensional data. This approach outperformed over traditional clustering methods and provided better accuracy, dimensionality reduction and actionable insights from easily interpretable geographic and customer behaviour patterns visualization.

5.3. Step 3: Construct an integrated marketing program that delivers superior value

5.3.1 Product Design related activities

In (S. Yang, 2023), the author states that conventional film and television technologies are failing to meet the requirements of the current market. The study emphasizes the need to use deep learning techniques, namely CNNs, for developing high quality film posters. The proposed system analyses posters based on characteristics such as theme, style, composition, colour scheme and setting. This enables the prediction of the effectiveness of a given poster, in engaging the target audience. It provides a valuable tool to film promotion teams, for identifying suitable posters for the targeted movie audience.

5.3.2 Promotion related activities

Customer Behaviour Prediction

Both (Sakthi & Sundar, 2024) and (Yuan, 2024) focus on the prediction of customer behaviours by analysing customer related data. In (Sakthi and Sundar, 2024), the authors investigate the customer purchase history, billing data, demographic data and service usage data in a deep learning model that combines dilated-DTCN and RNN architectures. This approach calculates convergence rates while keeping computational overhead to a minimum.

On the other hand, (Yuan, 2024) includes more sources of information in the analysis, e.g. e-commerce platforms, social media, customer relationship management systems and offline sales records to increase the precision of consumer behaviour predictions. The author employs an LSTM model to analyse the data and forecast browsing conversion rates, purchase rates, repurchase rates, cart abandonment rates and customer satisfaction levels. The results show how predictive analytics can be used to support decision making processes and thus help improve business performance, increase customer satisfaction, and enhance market position. The author recommends regular model updates incorporating real-time changes that may affect marketing strategies.

In (Goyal, 2023), CTR predictions are also made on the basis of the advertisement visuals along with the information about the advertiser, advertising space and category. The authors have proposed an end-to-end deep learning model (CNN) that operates on real data from a commercial advertising platform. This model identifies creative attributes from the creative images, combines them with the given advertisement details and predicts the chance of a click on the advertisement image.

In another paper that delves into the application of images, (A. Xu et al., 2024) apply deep learning to develop a decision support system for marketing management. The size and shape of products and the preferences of the brand are coded, using **a pre-trained CNN (ResNet-50),** while the sequence information and the browsing/purchase behaviour are encoded using a GRU neural network. The authors were able to take advantage of transfer learning to improve the efficiency of the model by fine tuning pre-trained models to achieve faster training time without compromising the flexibility to customize the model. The robustness of the system was tested across different datasets and the results were found to be favourable.

In the work of (Chopra & Raja, 2024), the problem of preserving the privacy of users in digital marketing and at the same time enabling effective customer segmentation is considered. As for the challenges, these are defined by the need for user control over personal data and the need to comply with laws such as GDPR[3] and CCPA[4]. To this end, the proposed solution presents a privacy-preserving user modelling framework based on deep learning techniques. Hyperbolic embeddings are used to ensure the structural integrity of user data while protecting against direct exposure of user interests in a hierarchical, low-dimensional space. Then the authors present a method of producing synthetic user data that adhere to real distributions with the help of Generative Adversarial Networks (GANs), which allows for accurate targeting without compromising privacy. From the description of Federated Learning, it is evident that model training happens on users' devices, such that personal data stays local, and only aggregated updates are shared. These technologies, when combined innovatively, can provide marketers with an effective way of modelling users accurately, while meeting the strictest principles of user privacy.

As an experimental work, (Wade Naidoo et al., 2022) aims at solving a primary problem in marketing – to induce real and sincere feedback from customers to understand how they feel towards the campaigns. The authors note that conventional approaches, including surveys, are inadequate due to biases such as dishonesty or social pressure. To overcome this, the study uses computer vision and deep learning to analyse facial expressions and identify emotions like happiness, anger, and surprise. Thus, the natural, real-emotional reactions of customers can be studied which can provide organizations with valuable insights into their customer's experiences. The approach could be useful in scenarios where capturing video frames can be practical, eg. social media, video games, etc.

[3] General Data Protection Regulation: European Regulation on the protection of personal data processing
[4] California Consumer Privacy Act: Californian Legislation for personal data usage/processing

Finally, (Aslan et al., 2022) is concerned with improving promotional strategies in large physical spaces such as shopping malls, parking structures, and sports stadiums to support targeted advertising. The authors designed a CNN model to distinguish the age and gender of people from video frames in real-time. Nevertheless, the approach is still experimental and requires the integration of other technologies, including video frame extraction, to work efficiently, which highlights the need for further improvement to make it practical and efficient.

Optimizing Marketing Strategies

In (Su et al., 2022), the authors designed a DL model, combining a DCNN and an attention-based LSTM model, that operates seamlessly from end to end, and is used to understand customers' buying behaviour, predict their preferences and help in effectively targeting marketing efforts in e-commerce platforms. The model gathers and cleans various user data e.g. textual and visual, and uses deep learning techniques to identify important characteristics. It classifies and labels users according to their activities on the internet, while compressing the characteristics that have been identified to reduce the dimensionality of the data and enable fast processing, which is important when providing real time decision support. The model uses these findings to suggest products or services that may interest users based on their identified preferences. Furthermore, the model **updates the marketing strategies** based on customer's behaviour and profile. For instance, it suggests budget friendly products to price sensitive customers or promotes new and trendy products to customers who are interested in new things. It also pinpoints high impact marketing strategies for instance exclusive discounts or time sensitive campaigns, e.g. hunger marketing, to evaluate their efficiency through performance indicators such as CTR, UI, and TSR.

In a similar way, in (Bala & Chitra, 2022), the authors collect data from real-time customer reviews and comments, star ratings, etc. However, they have not used this approach exclusively to treat marketing strategies as independent actions. Instead, they have

conceptualized these strategies as strategic factors that when integrated with other data, such as customer reviews, can offer a more accurate prediction of online product sales. The model is intended not only to define the best marketing actions in different situations, but also to define how these actions influence other factors. This provides a more holistic view of the marketing dynamics and hence, offers a better line of sight into what really works and what doesn't for improving sales.

In (Han et al., 2023) the authors follow a similar approach to privacy-preserving user modelling as in (Chopra & Raja, 2024), which was outlined in section "Customer Behaviour Prediction". However, this study extends the proposed framework by integrating Hyperbolic Metric Learning to form an integrated decision-making mechanism that precisely matches users to specific marketing campaigns. System evaluation demonstrated that this model is capable of accurately pairing campaigns with users who will likely engage in and accept the suggest offers, thus indicating its suitability for improving the effectiveness of targeted marketing strategies.

A growing focus, today, is the optimization of campaigns for Mobile Performance Marketing (MPM). MPM is a digital marketing strategy designed specifically for mobile devices such as smartphones and tablets. What makes MPM different from the rest is the performance marketing model, which is pay per conversion or pay per click. Real time bidding is at the core of MPM and is facilitated by Demand Side Platforms (DSPs). These platforms play the role of middlemen between the publishers who have the inventory to offer and the advertisers who are looking to target certain audiences. Through the use of sophisticated tools, the DSP guarantees that the ads are shown to the most likely customers, in order to increase the conversion rate and, therefore, the financial returns. To tackle the challenges of campaign selection in the context of MPM, an Intelligent Decision Support System (IDSS) is proposed in (Matos et al., 2023). This system uses a deep learning model (MLP) to predict the probability

of a user converting after seeing an ad. The model is designed for computational efficiency and can work with big datasets, which makes it suitable for the dynamic and data-rich environment of mobile performance marketing. In addition to this area, an experimental study (Bouzidi et al., 2022) suggests a DL model (LSTM) that includes localization features for the promotional marketing optimisation.

Lastly, there are several examples of the use of DL in real world industries including the banking sector (Reddy, 2022; Hematyar, 2022), agriculture (H. Yang et al., 2022) and catering businesses (Peng, 2022). (Reddy, 2022; Hematyar, 2022) and (H. Yang et al., 2022) present various deep learning models that are used to forecast real customer data and suggest specific promotional actions that increase the conversion rate while keeping the costs minimal. On the other hand, (Peng, 2022) provides a theoretical contribution to the understanding of the strategic importance of integrating deep learning solutions into the marketing function within the catering industry with an emphasis on the possible improvement in operational efficiency and customer relationship management.

In the end, two papers used real-world data from real businesses and large samples (Cui, 2024; Cai et al., 2023). (Cui, 2024) aimed at enhancing the effectiveness of marketing strategies for cross-border e-commerce stores which are characterized by challenges, such as increased competition, rising customer acquisition costs, and platform fees. The author proposed a Deep Convolutional Neural Network (CNN) for the prediction of the effectiveness of various marketing strategies. For example, the model can determine the effectiveness of combining two selected marketing strategies, the influence of various product categories on marketing results, and which search terms affect search traffic. The system was tested on real marketing and search data from a cross-border e-commerce company for two months. The results showed that the model could effectively learn and optimize the marketing strategies with high accuracy of 99.47% in determining the best outcome.

(Cai et al., 2023) aims to increase the likelihood of certain user actions within the context of a marketing budget setting. The goal is to improve the effectiveness of marketing campaigns by taking into account the long-term impact of budget decisions instead of using classic approaches that focus on users' immediate response. The authors proposed a new game-theoretic offline **value-based reinforcement learning approach** to this budget allocation problem and used mixed policies to solve it. This method simplifies the process by requiring only a constant number of policies, instead of an infinite number of policies to be produced and checked, and yet is nearly as efficient.

The system was trained and validated using a dataset which was developed from Alipay's online A/B testing[5] platform, and the data used for the training and validation set was collected from 4.2 million samples during the week of December 2020. The performance of the model was also assessed through real A/B testing involving tens of millions of users. The outcomes of the model revealed its efficiency that led to its adoption in a real-life marketing campaign.

5.4 Step 4: Engage Customers, build profitable relationships, and create customer delight

5.4.1 Enabling Tools for Customer Engagement

Chatbots and other dialogue enhancement tools

A main issue that companies encounter when implementing chatbots is that these tools cannot always comprehend the full meaning of the questions asked by the users which results in inappropriate or even misleading answers. This in turn annoys the customers and damages the trust they have in chatbot made recommendations which in turn, results in lost sales. To address this problem, (S. Zheng et al., 2023) design a deep learning algorithm (MH-DNN) into

[5] A/B testing, also known as split testing, is a method used to compare two versions of a webpage, app, or marketing campaign to determine which one performs better

an NLP system to enhance the chatbot's capability in identifying the intent, eliminate logical flaws and enhance the accuracy of the responses. This state-of-the-art model ensures that there is minimal misunderstanding and maximum interaction to deliver a more efficient and smoother customer conversation that can lead to increased conversion rates and brand equity. Furthermore, the experiments show that the system is highly accurate and requires less computing time, which makes it a practical and viable solution for businesses.

Another common issue that has been reported in the implementation of chatbot in customer service is the understanding of the user's intent related to specific industry domains where general NLP models may misjudge the use of certain terms. This can result in erroneous suggestions being made to the client, which in turn may lead to customer dissatisfaction and possibly, reduced sales. To solve this problem, (Altuama, 2023) proposed a NER model based on BiLSTM to design a tailor-made model for office products. This model is trained to understand the contextual relationships and the important components of a given query which in turn improves the intent detection. The experiments show that the system performed very well on real datasets, i.e. the Amazon office product search queries, and provided accurate outputs to the users, thus improving the effectiveness of the chatbot in increasing sales.

Finally, (Z. Xu et al., 2023) aims at understanding user's intent in a voice-based dialogue system for an electricity company. The proposed deep learning model integrates a multi-head attention mechanism with LSTM to improve the accuracy of the system for classifying short text sequences. This approach captures complex contextual relationships in user input with higher accuracy and efficiency than traditional models. Extensive simulations validate robustness of the system, demonstrating superior performance in real-world marketing applications for the specific industry. The improved intent recognition capabilities do not only enhance customer interactions, but also help businesses adjust personalized marketing strategies and increase customer engagement and revenue.

Recommendation Systems

A major issue in the tourism industry is to develop smart and accurate recommendation systems that can personalize recommendations according to user preference with minimal semantic ambiguity and time waste. Most current recommendation systems have limitations in incorporating dynamic user behaviours and various types of content which results in poor suggestions and uninterested customers. To overcome these constraints two sophisticated approaches have been suggested. (H. Yang & Ren, 2024) uses social and spatial data and process them in a DL model, combining ResNet and STGCAN, to make precise location-based recommendations exploiting user's social relationships and activities. (Wu & Liu, 2024) present a new visual search engine based on image searches, instead of text searches when looking for tourism products and experiences. The proposed model employs multi-modal data and transfer learning to build the CLIP-ItP model that enhances the recommendation accuracy even for novel and rare items. Both approaches enhance user participation and reduce the effort required in the search process, to increase the conversion rate on tourism e-commerce platforms.

Another important issue in the field of recommendation systems is how to model user's behaviour in a dynamic environment, incorporating user changes that matter. To this end, (Q. Liu et al., 2024) use several deep learning strategies to enhance recommendation accuracy and individualization. First, a transformer model is employed to learn the intricate correlations between user behaviours and product information. Second, a GAN is used to enhance the presentation of products, providing not only product descriptions, but also realistic representations of the recommended products with enhanced attractiveness. Then, an RL model is developed to learn from the users' feedback and iterate on the recommendations to ensure that the recommendation process is dynamic and personalized. The effectiveness of this multi-

step approach is also validated through experiments, and the results show that this approach outperforms conventional recommendation systems in terms of user engagement, conversion rate, and customer satisfaction.

Another emerging challenge in marketing in nowadays, is to guarantee that recommendation systems encourage the right consumption behaviour that is environmentally and socially responsible. The conventional recommendation models are designed to achieve high engagement and conversion rates without regards to the effects of promoting sustainable products. To this end, (Zhong & Yue, 2023) designed a DL-based recommendation system that incorporates sustainability factors into the recommendation model. Using an Inception CNN algorithm, the model improves the capability of the model to recognise user intent and suggest environmentally friendly and socially responsible products. This approach not only enhances the recommendation quality but also supports the concept of corporate social responsibility by steering customers towards more sustainable options. The experimental results show that the system achieves a good trade-off between the commercial and ethical goals, thus enhancing the user engagement and sustainability of the marketing activities in the long run. The company noticed a boost in the CTR by 30% and in conversion rate by 20% within the first six months of the system's introduction in everyday business, demonstrating in practise increased customer satisfaction and loyalty.

5.4.2 Systems for Customer Engagement

A key challenge in marketing these days, is understanding consumers' sentiments and creating emotionally powerful content that will engage the customer. To address this challenge, (Y. Li, 2024) used deep learning models to analyse e-commerce reviews and recognise the emotions underlying the sentiment. These insights become the bases for developing marketing

campaigns that are designed to elicit selected emotional responses, which in turn cause CTR and CR increase.

Apart from incorporating sentiment analysis for providing better emotional reactions, (Q. Zheng & Ding, 2022) proposed another sophisticated recommendation system that combines immersive marketing with graph neural networks for more personalized and engaging shopping experiences. The model tries to learn the user's Points of Interest (POI) by determining the products, services or content that the user is likely to be interested in, so that the recommendations are both relevant and compelling.

At the end, managing customers' heterogeneity is very important in the marketing process. Heterogeneity is defined as the psychological differences between consumers that cannot be captured through behavioural log analysis alone. Traditional approaches also rely on behavioural data including purchase history and site activity but do not include the cognitive and emotional factors that influence decision making thus leading to inaccurate customer segmentation. In (Niimi, 2024), the author uses multimodal deep learning and combines online product reviews (text data) with consumer demographic information, to enhance customer loyalty prediction. A comparison of different BERT-based models is performed in the study, which shows that the use of multiple data sources enhances the prediction accuracy and model robustness. These findings help organizations improve their strategies for personalized marketing, their management of loyalty programs, and their interaction with customers. The incorporation of other format of data, like videos, should be investigating in the future.

5.5 Step 5: Capture value from customers and create profits and customer equity

5.5.1 Capture Customer Lifetime Value

While e-commerce is becoming more and more popular, it is very important for each business to focus on the right customers and build lasting relationships with them. Most marketing approaches are not precise in predicting customer actions, classifying consumers, and optimizing strategies, resulting in funds being used ineffectively and potential revenue lost. The study of (Jamalpur et al., 2024) tackles exactly this issue, by employing deep learning and predictive modelling to identify Customer Lifetime Value (CLV) and help businesses classify customers and recognise potential behavioural changes. Therefore, based on CLV forecasts, businesses can better target their resources, create individual marketing programs, and develop strategies to keep customers and increase their lifetime value.

5.5.2 Create satisfied loyal customers

To further illustrate real world applications of deep learning in marketing, (Olamide Raimat Amosu et al., 2024) describes three case studies which demonstrate its potential. In the first case study, a company faced challenges in consolidated customer data because of its numerous product categories and global clientele. The company was able to create highly personalized recommendations by using deep learning models that were trained on data from purchase history, browsing behaviour, and demographic information. Also, these insights were used to enhance inventory management to minimize both stockouts and overstock situations. The company was able to reduce costs and increase operational efficiency.

The second case study considers a company that faced difficulties in the integration of data from in-store purchases, online shopping activities, and customer loyalty programs. The company developed a single customer view using deep learning models to personalize the customer journey across all platforms. This implementation enhanced online sales by 25% and in-store sales by 15%. The customers who received the personalized recommendations on the

company’s mobile app were more likely to visit physical stores and increase physical traffic and revenue. In addition, the real-time data processing enabled the provision of dynamic and personalized promotions to enhance customer delight and brand identity.

The third case study looks at a small retail company that was facing many difficulties because it had limited data and resources compared to larger companies. The company was able to develop sophisticated personalized marketing campaigns with the help of cloud-based deep learning solutions without the need to invest heavily in infrastructure. The company saw a 40% improvement in CTR and a 25% improvement in conversion rates within the first three months of the deployment. The DL system helped in the generation of relevant product recommendations and targeted promotions, which in turn increased customer delight, engagement, and retention.

These case studies show how deep learning is revolutionizing the practice of modern marketing and its potential to improve customization, supply chain management, and revenue enhancement regardless of the size of the business. Therefore, through the integration of DL, companies can enhance their operating performance, customer interaction, and sustainability in the digital marketplace.

Chapter 6: Deep Learning Techniques/ Algorithms/ Methodologies employed in Marketing

Deep learning is changing the digital marketing world by applying the principles of data analysis, automation, and personalized consumer experiences (Gazala Masood et al., 2022). In its capacity as a subset of artificial intelligence, it helps companies to analyse datasets and, therefore, interact with customers and make decisions more effectively. Search engine optimization, social media marketing, chatbots, predictive analytics, and targeted advertising have all been impacted by deep learning, which is still in the relatively early stages of its development. However, personalization is a major advantage, while privacy issues and ethical issues are major problems (Gazala Masood et al., 2022). Deep learning is, therefore, expected to become more entrenched in marketing strategies as AI technologies advance and affect the future of the marketing industry and the alignment between academic research and business applications.

To evaluate the progression of deep learning in marketing, this study analyses the increasing complexity of research conducted from 2021 to 2024, as in Figure 4.

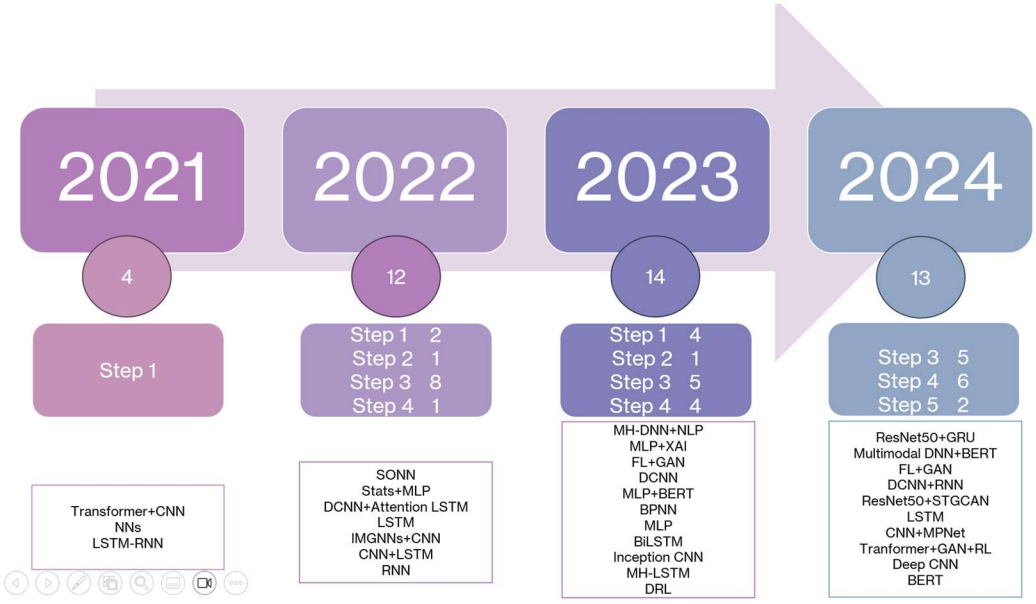

Figure 4: Distribution of articles through 2021-2024

In 2021, deep learning applications in marketing were relatively limited (Arafat et al., 2021; Benbrahim Ansari, 2021; L. Liu et al., 2021; Löwe, 2021), with most studies focusing on non-real-time implementations dedicated to marketing research, primarily analysing market trends, consumer sentiments, and behavioural insights.

By 2022, research had progressed significantly, integrating deep learning algorithms with statistical and machine learning techniques to enhance customer behaviour prediction and optimize marketing strategies (Aslan et al., 2022; Bala & Chitra, 2022; Bouzidi et al., 2022; Hematyar, 2022; Peng, 2022; Reddy, 2022; Su et al., 2022; H. Yang et al., 2022). This period also marked the introduction of real-world applications in sectors such as banking (Hematyar, 2022; Reddy, 2022), agriculture (Su et al., 2022), and catering (Peng, 2022), demonstrating a shift from theoretical models to practical implementations.

By 2023, the research landscape had evolved further, with an increasing focus on sophisticated chatbots (Altuama, 2023; Z. Xu et al., 2023; S. Zheng et al., 2023) and recommendation systems (Zhong & Yue, 2023). These models leveraged multiple deep learning techniques to understand conversational context, predict user intent, and personalize marketing efforts. A notable large-scale real-world implementation in 2023 enabled the real-time optimization of promotional strategies (Cai et al., 2023), highlighting the growing reliance on AI-driven decision-making in marketing.

This trend carried on in 2024 where the deployment of real-environment deep learning applications in various fields of marketing continued. The first systems for customer value prediction (Jamalpur et al., 2024) were introduced and used for personalized retention strategies. These developments highlight the growing importance of deep learning usage in predictive and prescriptive analytics, which allows for the improvement of customer engagement, but also the development of strategies that focus on retaining and evolving customer relationships over the long term.

A key outcome of this research is the increasing use of various combinations of deep learning algorithms for more marketing applications. Beyond relatively simple implementations of neural networks (NNs) and multilayer perceptron (MLPs) for classification and prediction, various forms of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks were applied to different types of data, including text, images, and natural language.

Various CNN architectures (Sakthi & Sundar, 2024), including dilated CNNs (Sakthi & Sundar, 2024), Inception CNNs (Zhong & Yue, 2023) and pre-trained DL models, such as ResNet50 (A. Xu et al., 2024; H. Yang & Ren, 2024) were used for complicated marketing problems. Also, (Shen, 2022) proposed a new approach for developing an advanced big data analysis and prediction system based on CNNs and distributed parallel processing. The importance of this approach is that it can improve the computational speed and scalability for the increasing complexity of data driven tasks. A five-layer system, referred to as DCNNPS, alongside a parallel optimization processing strategy act as the core of this system to improve the training efficiency. The effectiveness of this approach is supported by empirical evaluation on different datasets including MNIST, CIFAR-10 and Flowers where it achieves better accuracy and faster training time. This contribution is particularly important for industries that deal with high dimensional data, and it offers a systematic approach to avoiding computational bottlenecks and simplifying data processing flows. `

Some studies, that investigated CNNs also, recommended the use of CNNs in combination with transformers (L. Liu et al., 2021), MPNet (Wu & Liu, 2024), spatiotemporal graph convolutional networks (STGCAN) (H. Yang & Ren, 2024), and different variants of RNNs (Sakthi & Sundar, 2024) and LSTMs (Almutairi & Alotaibi, 2023; Bala & Chitra, 2022; Su et al., 2022) to develop better marketing strategies.

In the case of RNNs and LSTMs, (Sarkar & De Bruyn, 2021) investigated how LSTM networks are effective in direct marketing, for solving a critical issue in predictive modelling: the over-reliance on feature engineering. Most customer response models are constructed manually and, building them requires a good level of domain knowledge to design proper features; it is a time-consuming process, and it can also be biased. LSTMs, a kind of specialized RNNs, address this restriction by designing the network to learn long-term dependencies from sequential data. Because of this, LSTMs are especially useful for the sequential data that is characteristic of customer behaviour, and which has important temporal characteristics. The findings of the study also support this advantage such that LSTM models are not only better than traditional benchmarks but also comparable to expert-designed models in terms of accuracy. Their applications are not limited to direct marketing but include brand choice modelling, and clickstream data analysis, all of which are areas that heavily rely on sequential dependencies.

In Chapter 5: Marketing Activities/Tactics Exploiting Deep Learning Implementations, various implementations of LSTMs were employed in the research reviewed (Bouzidi et al., 2022; Jamalpur et al., 2024; Yuan, 2024) to help in promotion strategy optimization, consumer behaviour prediction, and CLV forecasting. Moreover, (Altuama, 2023; Z. Xu et al., 2023) investigated the use of BiLSTMs and multiheaded LSTMs to enhance the performance of chatbots. Furthermore, LSTMs were usually applied in combination with CNNs as described previously. RNNs were applied to classify consumer emotions from video frames (Wade Naidoo et al., 2022).

Most recent research has revealed the effectiveness of transformers like BERT in combination with other architectures like MLPs (Nouri et al., 2023) and multimodal deep neural networks (DNNs) (Niimi, 2024), in improving the performance of deep learning models

for natural language understanding, and generative adversarial networks (GANs) (Q. Liu et al., 2024) for the creation of very complex product images used for recommendation purposes.

Finally, more advanced deep learning concepts, including reinforcement learning and federated learning, have started to surface in marketing applications. To capture the dynamic and adaptive behaviour of consumers, reinforcement learning is growing in the application of consumer behaviour modelling (Cai et al., 2023; Cui, 2024; Yu & Liu, 2024), while federated learning is proposed as a technique to preserve the privacy of personal data which are used for marketing purposes (Chopra & Raja, 2024; Han et al., 2023).

Discussion

The results of this study reveal the changing role of deep learning in marketing activities and tactics, with a particular focus on certain steps of the marketing process. Figure 5 shows the distribution of the number of research papers along the marketing process steps. From Chapter 5: Marketing Activities/Tactics Exploiting Deep Learning Implementations, it is evident that the research articles are unevenly distributed across the five-step marketing process. Most studies are focused on Step 3, which emphasises on customer behaviour prediction and promotion strategy optimization, and Step 4, which emphasises on chatbots, recommendation systems and engaging systems. A large number of studies are also found to address Step 1, covering customer and market research issues and thus supporting the importance of consumer behaviour understanding, including how sentiments influence customer decisions, and technology acceptance.

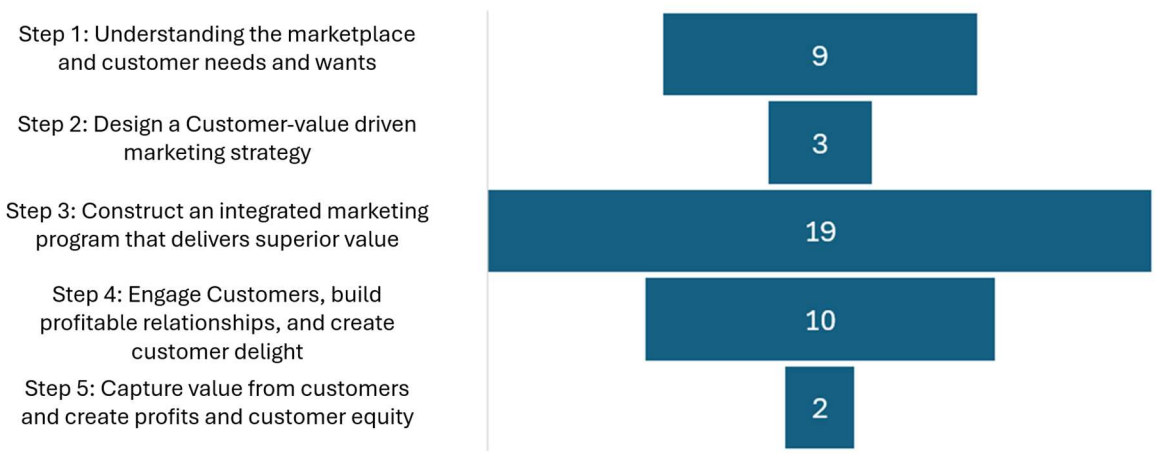

Figure 5: The distribution of the #papers along the Marketing Process Steps

The Blurring Boundaries in the Marketing Process Steps

A major problem when classifying the studies was the uncertainty in determining in which step of the marketing process each research study fitted best, which was especially evident for studies finally classified in Steps 3 and 4. This ambiguity is due to the real-time

processing capabilities made possible by deep learning algorithms that enable the integration of several marketing steps into one intelligent system. Many of the studies classified under Step 3 or Step 4 begin with the use of existing customer segmentations that are discussed in Step 2, followed by the prediction of behavioral responses to certain stimuli. Those studies that are assigned to Step 3 usually produce predictions that are useful for further strategic analysis or for designing optimal promotion strategies. But those that are assigned to Step 4 usually focus on personalized recommendations and systems that advance customer engagement and their design exploits consumer traits and behavior.

Deep learning has revolutionized marketing, and it seems the traditional five step marketing process is changing. The integration of Steps 2, 3 and 4 into one category, mainly in the digital marketing environments, captures the need for integrated real time decision systems. This shift needs a review of the existing marketing models to fit them to the fluid environment created by deep learning-based automation and prediction systems.

Real-time vs. non-real-time implementations

One of the most significant findings of this research is the specific use of deep learning features depending on the timing of the classification. For example, sentiment analysis and emotion recognition are used in two completely different ways.

First, in Marketing Research (Step 1) as, where deep learning models are employed offline or, in a non-real time classification settings, they are mainly used for the purpose of understanding how consumers' decisions are affected by their emotional state, in general.

Second, in Strategy Optimization and Customer Engagement (Step 3 and Step 4 respectively) real-time emotion identification brings more flexible usage, such as dynamic promotional strategies, dynamic recommendation systems and enhanced chatbots, that use customer emotion identification, to provide advanced experiences and engage customers in real-time environments.

The available deep learning algorithms can be adjusted to accommodate different needs and applications in the marketing process, depending on the problem at hand and its characteristics. Real-time processing and decision making, requires the use of dimensionality reduction and deep learning techniques adjusted to produce multilevel decisions, possibly engaging more computational power. On the other hand, non-real time processing and decision making, can elaborate the use of enormous datasets to analyse accumulated data in ways non-previously possible, thus enabling marketers to test new theories and acquire new knowledge on previously unlinked factors.

Experimental vs. Real-World Implementations

Another very interesting finding from this study is the type of datasets applied in the deep learning research for marketing purposes. Most of the reviewed studies used experimental data, such as publicly available repositories like Amazon[6] and Kaggle[7], rather than real data from company environments. Only a few of the studies employed actual company data, and even fewer considered real-life implementations and business performance. This difference indicates a gap between the theory and practice of the application of deep learning in marketing. The limited adoption of real-world implementations is a concern in regard to the external validity and replicability of deep learning models in marketing.

While experimental research is useful for theoretical development, it may not capture the full complexity of real-world consumer behaviour, market trends, and operational realities. Future work should aim to address this gap by promoting partnership between academia and industry to enable more empirical research using real company data and business contexts.

[6] Data Sets for Analytics | AWS Marketplace (https://aws.amazon.com/marketplace/solutions/data-analytics/data-sets#)
[7] Kaggle: Your Machine Learning and Data Science Community (https://www.kaggle.com/)

Future Considerations

The rapid growth of deep learning can be considered as the next step in the marketing strategy development. The most significant and promising change is the transformation of the recommendation systems to more sophisticated personal chatbot assistants that can handle natural language, real-time conversational context, and, therefore, provide personalized product and service recommendations. This evolution also highlights the importance for marketers to shift to deep learning and more generally AI enabled customer engagement strategies that are able to move from the simple static recommendations to more dynamic and contextual aware interactions and relationships, which are evolving in-time.

Last, but not least, while the integration of deep learning technologies into marketing processes increases, the issues of the ethical use of consumer data, the transparency of algorithms, and the reduction of bias will become more and more significant. It is crucial for marketers and researchers to make sure that the AI decision support systems are not only rational but also moral and acceptable to the consumers.

Conclusion

This study explored the use of deep learning in marketing activities by reviewing the most recent literature between 2021 and 2024. The study aimed at determining which marketing activities are enhanced by deep learning approaches, and also which deep learning algorithms and tools are used to support the different parts of the marketing process. The findings of the study reveal that deep learning has been applied across all steps of the marketing process as defined by Kotler.

Nevertheless, the majority of the research focus is given to Step 3 and Step 4 where experimental systems study consumers' behaviour and provide personalized insights that help in the development of promotion strategies. Some of the implementations are further developed to provide the full system that is capable of recommending products and strategies to enhance the consumer engagement, procurement, and brand identity.

In addition to determining which marketing activities are enhanced by deep learning, this study also aimed at identifying the deep learning algorithms that are employed to improve the various aspects of the marketing process. It can be seen that during this short time-period the applications of deep learning has evolved greatly. Initial research focused on more simplified applications, but recent studies focus on complex and multilayered approaches that are already transforming the marketing process. The application of deep learning, enable real-time identification and response to personal wants and needs, thus transforming the marketing process itself and providing more sophisticated systems than span through different steps of the marketing process at the same time. Never before, was it possible to address in real-time and with highly personalised and precise choices, the customers' needs.

A large number of deep learning models, such as CNNs, RNNs, LSTMs, Transformers and GANs and different combinations of them, have been employed in various marketing activities, tested and found to be effective. Marketing researchers are also using pre-trained

models like ResNet50 to reduce the time for adoption and to make necessary adjustments for specialised applications.

However, there are some limitations in this study. For the selection of the research articles only two search terms were used, those are ‘deep learning’ and ‘marketing’, and that choice may have limited the research analysis. A more encompassing search that would have included other marketing and deep learning search terms may have given a more extensive set of articles and would have allowed a more conclusive analysis of the field.

Future research should explore the intersections of deep learning and marketing in greater depth, identifying emerging trends and critical research gaps. Since the marketing discipline and deep learning technologies are rapidly developing, the marketing function needs to re-assess traditional perspectives and incorporate more adaptive, AI-based frameworks to maintain effectiveness in the online environment.

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