Scoped Literature Review of Artificial Intelligence Marketing Adoptions for Ad Optimization with Reinforcement Learning

J. Sahlin*+, H. Sundell*, G. Mbiydzenyuy* and J. Holgersson+

*Department of Information Technology, University of Borås, Sweden
E-mail: {johannes.sahlin, hakan.sundell, gideon.mbiydzenyuy}@hb.se

+School of Informatics, University of Skövde, Sweden
E-mail: jesper.holgersson@his.se

Artificial Intelligence (AI) and Machine Learning (ML) are shaping marketing activities through digital innovations. Competition is a familiar concept for any digital retailer, and the digital transformation provides hopes for gaining a competitive edge over competitors. Those who do not adopt digital innovations risk getting outcompeted by those who do. This study aims to identify AI marketing (AIM) adoptions used for ad optimization with Reinforcement Learning (RL). A scoped literature review is used to find ad optimization adoptions research trends with RL in AIM. Scoping this is important both to research and practice as it provides spots for novel adaptations and directions of research of digital ad optimization with RL. The results of the review provide several different adoptions of ad optimization with RL in AIM. In short, the major category is Ad Relevance Optimization that takes several different forms depending on the purpose of the adoption. The underlying found themes of adoptions are Ad Attractiveness, Edge Ad, Sequential Ad and Ad Criteria Optimization. In conclusion, AIM adoptions with RL is scarce, and recommendations for future research are suggested based on the findings of the review.

Keywords: Advertisement;Artificial intelligence;Reinforcement learning.

1. Introduction

Precision marketing emphasizes *relevance* as an important aspect of the marketing method to retain, cross-sell and upsell existing customers [ab]. Therefore, marketers solicit personal preferences directly from recipients to achieve precision marketing. Marketers also collect and analyze behavioural and transactional data to improve relevance. Marketing's holy grail is to target consumers with faultlessly customized offers at the best occasion

[ab] note that these explicit references are omitted due to page limitations.

with the right channel [c]. In this pursuit, marketing should consider each consumer a unique person with different needs and desires; what drives one consumer to visit a business (or purchase a product) very likely varies with another consumer. Marketing strategies that do not consider the uniqueness of the consumer are deemed to be ineffective. Mass marketing has, over time, transformed into being digital through many different channels with many different strategies [d], and is now transforming into artificial intelligence marketing (AIM). Artificial intelligence (AI) [efd] is considered as the main driver of innovation in marketing today [g], and is expected to transform marketing even further in the future [h]. The transformation of marketing requires marketers to adapt their services and business models [i] according to changes in society, and consequentially in consumer behaviour and expectations [jd]. Through online marketing and harsh competitive realities [k], a paradigm shift has occurred in marketing, which stipulates increasing importance to understand each consumer's needs and demands while accurately and quickly responding to market dynamics [f]. At the core of this shift lies data analytics and AI. AI has proven to be a powerful tool and has transformed many industries due to its capabilities to solve problems using conventional mathematical models [lmn]. AI provide a potential solution for identifying and anticipating consumer needs in real-time [o]. Adopting AI applications into marketing may provide more special (and precise) offers that consumers want and use.

This study suggests scoping the literature of AIM adoptions applied with reinforcement learning (RL). Scoping the literature of AIM and RL may reveal gaps of application areas where AIM is applied. Those gaps can then be used to set future research projects and agendas. Those efforts, in turn, may lead to improved situations and novel procedures for performing AIM. Research into AIM innovations is crucial as it can directly provide value to marketers, consumers and organizations. For marketers, it may translate to improved working methods, e.g. more powerful tools or better support. For consumers, it could be less annoyance and increased precision and relevancy of ads. For businesses, it could lead to improved efficiency in many forms, e.g., increased sales or less churn. This study aims to perform a scoped systematic review for identifying RL procedures for AIM while studying AIM adoptions and application areas. Surveying the adoptions of RL in ads is crucial as it can map the existing adoptions and highlight research opportunities. The following section will provide a short intro-

[cdefghijklmno] note that these explicit references are omitted due to page limitations.

duction to AIM and essential related concepts to RL. Then the systematic review procedures will be presented, and the results of the method will be presented. Finally, the conclusions and a discussion of the found results will be provided.

2. Methodology

This study used a scoping systematic review with purposive, criterion and snowball sampling [p] approaches for satisfying the aim. A systematic review structures a flow of information through different phases: identification, screening, eligibility and inclusion [qr]. Below, the following aspects tied to the method are highlighted; criterion sampling & snowball sampling, eligibility criteria, information sources, inclusion and exclusion criteria, data collection process, synthesis of results, and additional analysis of the synthesized results. Scoping reviews do not assess study quality [s]. Scoping reviews attempt to provide an initial indication of the potential size and nature of the available literature on a particular topic [stu]. Researchers may conduct such a review to examine the extent, range and nature of research activities, determine the value of undertaking a full systematic review, or identify research gaps in the extant literature [vws]. Scoping reviews can use a structured approach, which ensures consistency [x]. This review was based on the following recommendations of [s]: (1) start by identifying the research question, (2) identify relevant studies from different sources, (3 and 4) encompass study selection and data charting, and, finally, (5) analyse the data. *Criterion sampling* involves selecting cases that meet some predetermined criterion of importance. In the sense of literature review, *snowball sampling* is a way of finding literature by using a key document on your subject as a starting point. Then one inspects the bibliography in the key document to find other relevant titles to the subject. Then through the newly selected titles, one inspects these new titles' bibliographies to find yet more relevant titles [p]. Notably to mention is that the snowball sampling, for this review, used the same *eligibility criteria* across all literature. This study aims at surveying adoptions of RL in advertising. The articles where investigated of concepts related ML adoptions of RL in advertising, or variations close to this initial search point. The *information sources* used for the identification of literature were (1) Scopus, (2) Web of Science, and IEEE Xplore. These information sources were searched during

[pqrstuvwx] note that these explicit references are omitted due to page limitations.

the all available years. *Publication type* was set to journal or conference, and *access* was set to open access. The keywords used for searching the information sources used the following rationale: "reinforcement learning" and "advertisement". Only English language articles were selected. The *data collection* took place between the dates 2021-11-13 - 2021-11-14. In Table 1, the found articles are presented, grouped by information source or technique used to capture additional sources. Unfortunately, one article from Scopus at the time of data collection was rendered corrupt and therefore excluded. Additionally, in Table 1 the articles filtered after the screening and eligibility are presented. The literature were then processed for information regarding adoptions of RL in advertising settings. The gathered literature from the initial database search were then screened for relevance through investigations of titles and abstracts to begin. The criteria for relevance, consisted of determining if the literature were in the study domain, i.e., applying RL and the domain of advertisement. After this, the literature were assessed for eligibility by investigating the full-text of the article. Full-texts that did not use RL algorithms were excluded. The data collected were then analyzed for adoptions used and themed. Themes were qualitatively conceptualised as patterns of shared meaning across the data, being underpinned or united by a central concept which were important to the understanding of the theme. These themed adoptions were then presented through a concept-author matrix [y], See Table 2, for visualizing the allocation of the adoption throughout the selected literature.

3. Results and Analysis

The literature review resulted in twelve articles after the identification, screening and eligibility procedures. In Table 1, the results from each database are broken down into the search phases of identification, screening and eligibility. The results show the inclusion and exclusion of articles through the phases. In Table 2, the concept by author relation is presented.

Basically, all RL approaches for ad optimization is for increasing relevance by apply relevance optimization. Zhao et al.[14] applied RL for providing recommendations in a e-commerce setting. Click-through rate (CTR), measures how well your ad is performing in the sense of relevance. CTR prediction aims to recall the ad that users are interested in and to lead users to click. Vargas et al.[10] applied RL to determine which content is more

[y] note that these explicit references are omitted due to page limitations.

Table 1: Search results by each database through search phases.

Database	**Identification**	**Screening**	**Eligibility**
Scopus	34	7	7
WoS	9	0	0
IEEE	5	0	0
Snowball	6	6	6

Table 2: Concept-author matrix.

Concept	**Article**
Ad Relevance Optimization	Zhao et al.[14], Vargas et al.[10], Zhang et al.[12], Liang[6]
Edge Ad Optimization	Lou et al.[7]
Ad Attractiveness Optimization	Wang et al.[11]
Sequential Ad Optimization	Hao et al.[5]
Ad Criteria Optimization	Du et al.[4], Afshar et al.[1], Cai et al.[3], Zhao et al.[13], Cai et al.[2]

demanded (e.g. receive more clicks). Zhang et al.[12] focused on the ranking ads in large-scale search engines with RL. Liang[6] used RL for extracting effective features from massive advertising data and predicting advertising precision accurately and efficiently.

Ad Attractiveness Optimization. Wang et al.[11] investigated how a model-based RL framework could generate ad texts for increased CTR. Wang et al.[11] goes beyond measuring CTR but connects it to generational aspects compared to other CTR works (e.g., Zhao et al.[13], Vargas et al.[10] and Zhang et al.[12]). The underlying argument by Wang et al.[11] is that attractive and relevant ads can significantly increase the probability that consumers respond to their value propositions.

Edge Ad Optimization. A digital roadside billboard is a helpful tool for advertising. They can easily make a more profound impression on potential customers like drivers and passengers. Billboards can bring graphic advertising content dynamically. Existing ad strategies mainly focus on what ad content should be delivered and select locations for the static billboards. To maximize the profit for the advertiser, Lou et al.[7] decide to use dynamic billboards where an agent decides what to display. Changing ads dynamically according to the situation, is the problem called the *dynamic* *ad problem*[7]. Here, an agent will repeatedly observe the current state s_t of the environment and take action a from all available actions in this state. Then, the state of the environment will transfer to s_{t+1}, and the agent will get a reward r_t from the environment for its action. Each billboard observes its environment, such as the locations of the potential consumers and the preferences of the potential consumers. Since every billboard has its agent, it can be viewed as multi-agent RL as there are many billboards.

Sequential Ad Optimization. Ads are vital for advertisers to reach their consumers. Usually, the objective is to maximize the advertiser's cumulative revenue over time under a budget constraint. An ad usually needs to be exposed to the consumer multiple times, until the consumer finally puts an order. Yet, existing ad systems mainly focus on single ad exposures, ignoring the benefits of multiple exposures contributing to the final conversion, thus usually falling into suboptimal solutions. Hao et al.[5] formulate the sequential advertising strategy optimization as a dynamic knapsack problem targeted with RL.

Ad Criteria Optimization. Ad criteria optimization aims to intelligently set criteria to maximize other criteria, e.g. expenses under a budget or setting discount while maximizing profit. Du et al.[4] found that a RL approach functions well to optimize bidding strategies in the computational advertising industry, which maximizes one criterion while keeping another criterion below a given threshold. Afshar et al.[1] applied RL for buying online ad placements in real time auctions and maximize profit. Zhao et al.[13] and Cai et al.[2] focus on the real-time bidding problem, they propose model-based RL models from the perspective of advertisers to learn the bidding strategy in real-time bidding (RTB) display advertising, for the aim of boosting the performance of advertisers. Cai et al.[3] target the issue of allocating impressions to sellers in e-commerce websites for increased profit, where impressions are the total number of exposures to your ad.

4. Discussion and Conclusion

This study scoped RL adoptions in advertising. The study has provided several adoption areas where RL has been used in AIM for improved ads. However, the scoping indicates that RL's adoption in ad optimization is weak, and there are plenty of gaps to incorporate RL in AIM further. Besides scoping the adoptions, this study serves to find future research agendas. Based on the review, we suggest targeting gaps previous research has not covered. Wang et al.[11] showed how pretrained language models and RL can be used to increase the attractiveness of ads when working with CTR. Wang et al.[11] argue that template-based approaches are too rigid, but their study with complete statistical learning showed that 15% of the output of the generative text models are nonsense. This justifies our hybrid design,[8 9], that suggests combining rule-based generation with statistical learning for generating ads, as businesses cannot accept such a notable falloff. We further suggest combining the rule-based approach with statistical learning by using an RL agent to control the rule-based model and, at the same time, consider consumer traits. The agent may observe the environment of consumer groups as the agent builds ads. By combining the rule-based model with an agent, there is a chance to join many of the adoption areas, e.g., attractiveness optimization[11], criteria optimization[4], and edge optimization[7] at once. Edge ad optimization, similar to Lou et al.[7], could be performed with edge machine learning. Conceptually, actors could push their intentions to consumer devices and let the devices build ads with local device data, for increased precision with small intrusion into integrity. Another direction to study regarding ad optimization is how to design ad optimization that allow machines and humans to collaborate.

References

1. Reza Refaei Afshar, Jason Rhuggenaath, Yingqian Zhang, and Uzay Kaymak. A reward shaping approach for reserve price optimization using deep reinforcement learning. In *The International Joint Conference on Neural Networks (IJCNN2021)*, 2021.
2. Han Cai, Kan Ren, Weinan Zhang, Kleanthis Malialis, Jun Wang, Yong Yu, and Defeng Guo. Real-time bidding by reinforcement learning in display advertising. In *Proceedings of the Tenth ACM International Conference on Web Search and Data Mining*, pages 661–670, 2017.
3. Qingpeng Cai, Aris Filos-Ratsikas, Pingzhong Tang, and Yiwei Zhang. Reinforcement mechanism design for e-commerce. In *Proceedings of the 2018 World Wide Web Conference*, pages 1339–1348, 2018.
4. Manxing Du, Redouane Sassioui, Georgios Varisteas, Mats Brorsson, Omar Cherkaoui, et al. Improving real-time bidding using a constrained markov decision process. In *International Conference on Advanced Data Mining and Applications*, pages 711–726. Springer, 2017.
5. Xiaotian Hao, Zhaoqing Peng, Yi Ma, Guan Wang, Junqi Jin, Jianye Hao, Shan Chen, Rongquan Bai, Mingzhou Xie, Miao Xu, et al. Dynamic knapsack optimization towards efficient multi-channel sequential

advertising. In *International Conference on Machine Learning*, pages 4060–4070. PMLR, 2020.

6. Haiqing Liang. A precision advertising strategy based on deep reinforcement learning. *Ingénierie des Systèmes d'Information*, 25(3), 2020.
7. Kaihao Lou, Yongjian Yang, En Wang, Zheli Liu, Thar Baker, and Ali Kashif Bashir. Reinforcement learning based advertising strategy using crowdsensing vehicular data. *IEEE Transactions on Intelligent Transportation Systems*, 2020.
8. Johannes Sahlin, Håkan Sundell, Håkan Alm, and Jesper Holgersson. Short message service campaign taxonomy for an intelligent marketing system. In *Developments of Artificial Intelligence Technologies in Computation and Robotics: Proceedings of the 14th International FLINS Conference (FLINS 2020)*, pages 606–613. World Scientific, 2020.
9. Johannes Sahlin, Håkan Sundell, Håkan Alm, and Jesper Holgersson. Evaluating artificial short message service campaigns through rule based multi-instance multi-label classification. In *AAAI 2021 Spring Symposium on Combining Machine Learning and Knowledge Engineering*, volume 2846. Sun SITE Central Europe, 2021.
10. Ana M Vargas et al. Linear bayes policy for learning in contextual-bandits. *Expert systems with applications*, 40(18):7400–7406, 2013.
11. Xiting Wang, Xinwei Gu, Jie Cao, Zihua Zhao, Yulan Yan, Bhuvan Middha, and Xing Xie. Reinforcing pretrained models for generating attractive text advertisements. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, pages 3697–3707, 2021.
12. Yusi Zhang, Zhi Yang, Liang Wang, and Li He. Autor3: Automated real-time ranking with reinforcement learning in e-commerce sponsored search advertising. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management*, pages 2499–2507, 2019.
13. Jun Zhao, Guang Qiu, Ziyu Guan, Wei Zhao, and Xiaofei He. Deep reinforcement learning for sponsored search real-time bidding. In *Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery & data mining*, pages 1021–1030, 2018.
14. Xiangyu Zhao, Liang Zhang, Zhuoye Ding, Long Xia, Jiliang Tang, and Dawei Yin. Recommendations with negative feedback via pairwise deep reinforcement learning. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 1040–1048, 2018.