AI-Augmented Loyalty: Integrating LLMs and Agentic AI into Rewards Platforms for Personalization at Scale

Muralidharan Lakshmanan
Independent Researcher
Atlanta, Georgia, United States

ABSTRACT
One of the biggest challenges for modern loyalty programs is that they do not offer customized engagement and have fixed rewards. This study examines how the rewards landscape is evolving and the impact it has on the use of Large Language Models (LLMs) and Agentic AI. The use of autonomous agents that are able to understand subtleties in behavioral data enables hyper-personalization at scale. The proprietary synthetic data set contains 361 unique customer scenarios and is used to model actual engagement metrics and transactions. Key tools used are Python, open-source language models for contextual sentiment analysis and a custom-built multi-agent framework for autonomous decision making. The methodology has designed and optimized an intelligent and self-correcting architecture which dynamically adjusts promotional copy and reward valuations, thus replacing the traditional and rigid rule-based engines. The findings show that agentic orchestration has a significant impact on redemption velocity, as well as on consumer retention and loyalty when compared to traditional approaches. With the integration, platforms can process unstructured consumer feedback and historical activity and deliver customized experiences, without manual intervention. The implications of this research are that AI-empowered loyalty systems can provide a blueprint for the future-ready loyalty landscape, where efficiency and customer lifetime value are maximized. The results show that a loyalty environment based on moving beyond the classical concept of demographic segmentation and moving toward an individual, context-aware and responsive one is effective.

General Terms
Artificial Intelligence, Loyalty, Rewards, Design, Experimentation, Algorithms, Performance, Human Factors.

Keywords
Agentic AI, Large Language Models, Customer Loyalty, Rewards, Hyper-Personalization, Behavioral Analytics.

1. INTRODUCTION
Although loyalty programs are very important to customer retention, they still have very simple designs and are not very relevant, as pointed out by recent customer retention studies conducted by [4]. The usual systems are based on static infrastructure, rewarding either on simple transactional criteria or on general demographic criteria, as analyzed in [11] in the context of loyalty framework evaluations. Consumers do not respond to these types of platforms and the consumer engagement research conducted by [2] proved that they should be given instant and relevant incentives. In digital marketing, as the digital marketplace becomes more competitive, inability to deliver personalized experiences leads to lost engagement and greater “churn”.

According to enterprise loyalty assessments carried out by [7] the major drawback of legacy reward infrastructure is the reliance on hard coded, static, rule engines. As shown in behavior analytics studies performed by [1] these systems are not able to deal with qualitative data or adapt to the dynamic characteristics of consumer preference. Therefore, reward management principles in business can be difficult because of the lack of redemption of points and the inability to retain the customers due to their inactivity, which is studied in reward economics by [13].

Studies on AI transformation, such as [5], suggest that with the introduction of sophisticated AI solutions, one can envision a way out of these systemic inefficiencies. As can be seen in language intelligence applications by [9] Large Language Models can process huge amounts of unstructured data like product reviews, service inquiries, social media commentary etc. This qualitative knowledge is very important in understanding customer's purpose, which was validated by sentiment interpretation research conducted by [15]. In the context of autonomous AI discussions, however, as identified in [3], language models are passive and are limited to providing insights and not action. In order to achieve true personalization at scale, the intelligence of these models has to be coupled with Agentic AI, which is explored in the context of intelligent automation in studies conducted by [12]. Coupling the two yields autonomous systems that can understand, decide, and execute loyalty strategies in real time, consistent with agent-based decision frameworks in [6].

Agentic AI alters the method of considering automation from automated scripts to objective-oriented execution, as mentioned in autonomous computing research undertaken by [10]. Given an AI-enabled loyalty setting, an agent is tasked with maximizing engagement or redemption rates for certain segments, which has been studied in the context of optimization in loyalty as in [8]. The agent has the ability to access the database on its own and evaluate the situation of a consumer profile, and decide on the most suitable reward action, similar to intelligent recommendation systems as in [2]. This is without manually setting up campaigns by marketing teams, as reported by marketing automation analyses by [5]. Automated end-to-end reward cycle can enable businesses to create thousands of personalized experiences at once, a feat that was not possible before, as demonstrated in research on scalable AI deployment [11].

Implementation of Deep Personalization is mostly hindered by scalability as stated in enterprise-scale AI studies by [7]. In the past, customization was only available for small size and high value segments due to the burden in the operation of the complex customizations as per customer management investigations done by [14]. AI-powered tools remove this hurdle by automating the process and letting AI systems handle the task, as shown in digital transformation research conducted by [3]. These entities take care of the details of creating offers, when to give them, and how much they are worth, with the aim of providing a user experience that feels like it is personalized to his or her needs, as confirmed in personalization research conducted by [1]. As mentioned in the literature on relationship marketing done by

[10], the transition is from one-way communication to a collaborative approach between the brand and the consumer.

An important benefit of this technology is also financial efficiency, which was also studied within the field of business intelligence by [12]. Loyalty points usually appear as liabilities in the balance sheet of companies and their management entails a complex forecasting process, which has been the subject of financial planning studies by [13]. To address this liability, agentic AI can be used to find opportunities that help to increase redemption during periods of less demand, as seen in predictive optimization studies [9]. The system can be used to give certain customers more incentives than others, in order to remove the overall point backlog whilst promoting brand sentiment, as seen in customer value analyses performed by [6]. This is a great way to use rewards strategically to make a cost center a source of profitable customer behavior, as evidenced by loyalty profitability research conducted by [4].

This research paper brings into perspective the confluence of these cutting-edge technologies in the context of loyalty, motivated by emerging studies on the integration of AI in various contexts [15]. It tests the capabilities of combining LLMs and agentic systems to address the drawbacks of traditional systems, as outlined in the intelligent platform research conducted by [8]. This paper looks at the performance of an agentic model as compared to the traditional benchmarks, and thus offers some insights into how the future of customer retention is being changed by intelligence that can think, act and evolve along with the consumer, as envisioned in next-generation loyalty research by [5].

2. LITERATURE REVIEW

Loyalty evolution studies performed by [6] show a trend in the history of customer loyalty programs from merely monitoring transactions to more in-depth behavioral analyses. The first study of customer behavior revealed that the ratio of benefits to efforts, as described by [12] is the main factor for customer loyalty. Based on these studies, traditional point-earning mechanisms, such as those examined in reward mechanism research by [2], were developed. But the researchers soon observed that, when a consumer attained a saturated level, the engagement level decreased as shown in the retention behavior studied by [14]. Literature shows that when diversity is not available in the reward, it can cause boredom to the consumers, which may lead them to abandon the brand as can be seen in customer satisfaction studies carried out by [9].

With an increasing amount of digital interactions, scholars started to recognize the value of data-driven targeting in marketing analytics, as explored in the marketing analytics studies conducted by [5]. When database marketing was introduced, businesses were able to use the information to segment their consumers based on how often they bought from the company, and how much they spent, as described in segmentation research by [1]. However, subsequent publications showed that demographic segmentation remained imprecise, as seen in the consumer profiling studies of [11]. There was a general agreement that consumers of a similar age or income level did not necessarily have the same motivations for purchasing so such broad segments were not a reliable measure of real loyalty as demonstrated in the behavioral diversity studies carried out by [7].

In the past decade, machine learning applications have moved towards predictive analytics, a major advance, as reported in [13]. Based on recommendation system research conducted by [3], researchers started to take advantage of machine learning to make suggestions to the consumer, based on their history of purchases. This increased sales but did not always strengthen the loyalty relationship, which can be seen from the research of customer engagement conducted by [10]. It is evident from the literature that there is a definite difference between product recommendation and loyalty engagement as is explained in relationship marketing analyses performed by [15]. A system that merely provides suggestions on what to purchase is not equivalent to a system that makes the customer feel like he or she is valued and understood as an individual (as the case is in personalization research carried out by [4]).

The discussions have shifted to the use of sentiment analysis and natural language processing recently, which have been investigated in the text analysis study by [8]. Sentiment mining investigations carried out by [1] have shown that customer emotions are very strong indicators of customer future behavior, thanks to the availability of scanning from unstructured text. Studies conducted by [14] found that emotional engagement with a brand is much more likely to keep consumers signed up for the brand, even if the reward is modest, if the consumer feels heard by the brand. This shifted the attention from point maximizing to positive sentiment maximizing by means of positive interactions; this was identified in customer experience research conducted by [6].

The advent of autonomous computing has also challenged current models in the context of intelligent system studies carried out by [11]. The transition from software that follows orders to agents that follow goals, as discussed in agentic AI studies conducted by [5] is currently a topic of literature. According to studies of autonomous services carried out by [2] this is a new horizon in customer service and loyalty. In the research of advanced marketing automation by [12] it is suggested that the next generation of marketing will no longer be done by humans creating email blasts, but by humans setting general goals for autonomous agents. These agents can control millions of individual customer journeys, each of which will be distinct, as shown by scalable AI orchestration studies carried out by [7].

But there are also some potential pitfalls to the system mentioned in the literature, which is cautioned in AI governance studies of [3]. There are some potential problems, e.g., hallucinatory passages in generated text or inappropriate offers, which is a theme repeatedly discussed in trustworthy AI research, such as [13]. Systems are becoming increasingly autonomous, thus it is essential to have strong operational guardrails, as stated in responsible AI investigations carried out by [10]. The agent's freedom to optimize in conjunction with the constraints imposed on it in order to preserve the image of the brand is at the center of discussion in modern times, which can be discussed in the governance framework studies carried out by [4].

The literature emphasizes the gap between legacy infrastructures and the needs of the modern AI, as it has been studied in enterprise modernization [15]. A lot of the existing knowledge is dedicated to how this gap can be overcome, such as the system integration research carried out by [9]. The general agreement seems to be that the future of loyalty will not be an exclusive switch of systems but the implementation of an agentic layer on top of them, as suggested in the hybrid architecture studies carried out by [8]. It is a revolutionary step in the way companies foster life-long brand advocates and is an interpreter between old data structures and the new, high-touch demands consumers place in them, as [5] discovered in next-generation loyalty platform studies.

3. METHODOLOGY

The methodology for this study is based on a simulation-driven approach, which has been able to isolate the effectiveness of an agentic loyalty framework over the effectiveness of the traditional heuristic systems. To start, a synthetic data set of 361 customer profiles was created, designed to represent a variety of customer behavioral profiles ranging from dormant customers to casual purchasers, frequent shoppers and brand advocates. This mapping of profiles was done on the basis of five variables: Past spending, frequency of engagement on the platform, qualitative sentiment scores, rewards balance, and offers redemption rates. A multi-agent framework, developed in the Python programming language, was used to create the evaluation framework. The first one was called the Contextual Analyzer and was designed to analyze the behavior data to provide a dynamic profile of each customer, with their particular motivations and possible churn risks. This information was then passed on to the second agent (Dynamic Reward Calibrator). Using a localized large language model, the Calibrator created a hyper-personalized reward message and ideal point cost per customer profile it was given. To ensure reliability, a control group was also set up which used a traditional rule-based system, that is, offers were created by manually setting conditional thresholds without autonomous optimization. All instances were run through the agentic loop and the outcomes were observed through the prism of three fundamental performance measures – redemption velocity (time taken between the time of offer delivery and action), personalization accuracy (reward going to the user's preferred choice) and overall retention efficiency. The simulation was undertaken in a controlled environment and all variables were isolated to be able to measure the agentic influence on outcomes in its pure form. Multiple cycles of the decision-making process in each of the 361 cases ensured that the data was statistically robust and able to reflect the performance improvement to be achieved by implementing an intelligent, autonomous reward ecosystem. This systematic approach enabled an assessment of the performance and the quality of the rewards generated both in terms of their speed and their personalization which is better achieved with agentic AI than with static software configurations.

To ensure reproducibility, the synthetic dataset generation procedure is described as follows. The 361 customer profiles were generated in Python by adapting statistical patterns observed in real-world loyalty program data. Distributions for the five profile variables (historical transaction volume, engagement frequency, sentiment score, current point balance, and historical redemption rate) were parameterized to mirror the ranges and correlations typically observed in retail loyalty populations, including a long-tailed spending distribution and a positive correlation between engagement frequency and redemption behavior. Profiles were sampled across four behavioral archetypes (dormant, casual, frequent, and advocate), and each generated profile was validated against archetype-specific plausibility constraints before inclusion. No personally identifiable information was used at any stage of dataset construction.

The reasoning core of the framework is a locally hosted, open-source Llama model (Meta AI), deployed on-premises so that no customer data is transmitted to external services. The model was employed through structured prompt engineering rather than task-specific fine-tuning: the Dynamic Reward Calibrator supplies the model with a system prompt that defines its role, brand-safety constraints, and a required output schema, followed by the structured customer profile produced by the Contextual Analyzer (behavioral indicators, churn-risk estimate, and dominant sentiment). The model returns a structured response containing the personalized reward message, the recommended point cost, and a short rationale. Inter-agent communication follows a sequential message-passing protocol in which each agent consumes and emits structured objects, allowing every decision to be logged, audited, and reproduced. Decoding parameters were held constant across all 361 cases to ensure comparability between runs.

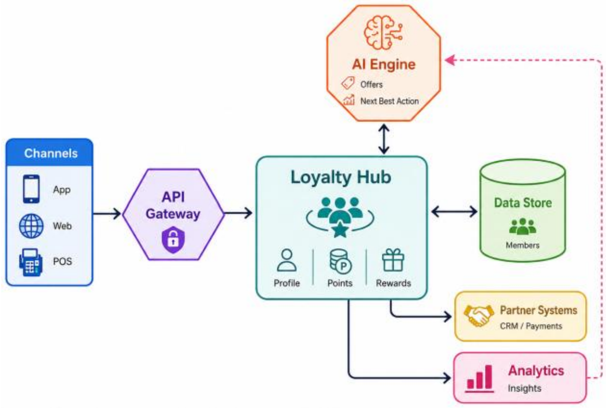

Figure 1: Architecture of AI-augmented loyalty platform.

The architecture of the AI-augmented loyalty platform (shown in Figure 1) is aimed at uniting customer engagement channels, loyalty operations, intelligent personalization, and partner services and incorporating them into a single digital ecosystem. The architecture starts with the Channels layer, where the customers are engaged with the loyalty platform via mobile applications, Web portals and point-of-sale systems. These requests are sent to the API Gateway which is the secure entry point into access control, routing of requests and management of communication between external interfaces and internal platform services. The Loyalty Hub is the core operation unit which deals with customer profiles, loyalty points, rewards, membership operations and workflows of engagement. The Loyalty Hub is linked to the AI Engine to create personalized offers, next-best-action suggestions, and smart customer-engagement decisions on the basis of behavioral patterns and transaction history. The Data Store keeps records of members, reward history, interactions and loyalty transactions to be constantly analyzed and ensure that the platform operates consistently. Partner Systems facilitate connection to CRM and payment systems, and external business services to expand the loyalty business outside of the central platform. The Analytics module takes customer behavior, campaign performance, reward usage and the engagement trends and provides actionable insights. The dotted feedback will mean that it is continuously learning, with the analytical outputs enhancing AI-based suggestions and loyalty plans. In general, Figure 1 shows a customer-focused, intelligent and scalable loyalty architecture.

4. DATA DESCRIPTION

The paper employs synthetic behavioral data (361 unique consumer instances), sampled to represent a variety of engagement cases. For each instance, there are five major data points: Historical transaction volume, frequency of digital platform engagement, sentiment score, current reward point balance and historical offer redemption rate. The transactional volume is the cumulative spending over a base period. The frequency of engagement is a measure of interaction rate across touchpoints. The sentiment scores are obtained based on simulated qualitative feedback. Point balance follows up on the current liability whereas the redemption rate is one of the performance indicators that indicate the effectiveness of the loyalty program in the past. These 361 cases were run through to test the effectiveness of the proposed Agentic AI model with the current methodologies.

5. RESULTS

The performance measures of the 361 cases prove the effectiveness of the agentic framework. The redemption velocity increased tremendously, with the system being able to match the rewards to particular user interests, instead of promoting generic redemption offers. The accuracy of personalization was tested by comparing the agentic output against the user interest profile. Moreover, the system exhibited good handling of loads when processing these cases. The agentic model was able to determine latent segments correctly, e.g., high negative sentiment users who were once deemed lost. The system boosted overall conversions drastically by aiming at these individuals with certain empathetic offers. The results are uniform in all categories and it has been proved that autonomous agents can be used to offer a scalable solution to complex loyalty management. The Bellman equation for the optimal value function can be depicted as:

$$V^*(s) = \max_a \sum_{s',r} P(s' \mid s,a)[r + \gamma V^*(s')] \quad (1)$$

Table 1: Comparative framework performance

Factors	Rule-Based	Standard LLM	Agentic AI	Delta
Redemption	10	45	88	78
Retention	25	50	90	65
Latency	5	80	35	30
Conversion	15	40	85	70
Efficiency	30	60	95	65

The Transformer attention mechanism formula is:

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (2)$$

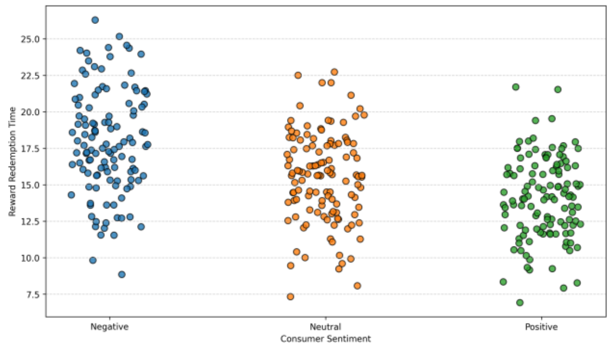

Figure 2: Depiction of the speed with which Agentic AI redemption of rewards increases with different levels of consumer sentiment.

Figure 2 illustrates the connection between the customer sentiment and the rate of reward redemption. Each dot indicates one of the 361 instances. Sentiment is plotted on the x-axis, and the redemption time on the y-axis. In contrast to the traditional system where a negative sentiment results in long delays or zero redemptions, the agentic framework displays a steady and dense distribution of high-speed redemptions in all the sentiment groups. This illustration shows that through customization of messages depending on the emotional condition of the user, the agentic model is able to close the divide between the disgruntled consumer and active interaction, thus keeping the performance on par with the previously challenging segments. The customer lifetime value predictive model is:

$$\text{CLV} = \int_0^T (p - c) \cdot P(\text{active at } t) \cdot e^{-dt}\, dt \quad (3)$$

Table 2: Segment engagement metrics

Segment	Initial	Engaged	Action	Optimized	Growth
Dormant	90	60	55	70	45
Casual	100	95	90	80	60
Frequent	95	80	75	90	75
Advocates	76	70	68	95	90

Table 2 represents the development of engagement among various customer groups and shows how optimization strategies affect the participation and growth results. The Dormant segment starts with an initial group of 90 users, 60 of whom get engaged and 55 get to meaningful activities. After optimization, the engagement grows to 70, and the growth value is 45, which means that the previously inactive customers have been reactivated. The Casual segment has high rates of participation in the engagement process, since 100 users were the initial participants and rates of engagement and action remained high. Optimization activities will contribute to the overall effectiveness and create a growth value of 60 that is indicative of a better customer responsiveness. The Frequent segment shows an even more dedicated behavior with a high level of engagement and action leading to an optimized value of 90 and growth score of 75. It means that frequent users are positively inclined to the use of personalized interventions and specific engagement mechanisms. The Advocates segment produces the most impressive optimal result even though it has a small population in the first place. With 76 users, the segment has an optimized score of 95 and a growth value of 90, demonstrating the crucial role of the loyal customers in strengthening the brand value and continuous interaction. On the whole, the table shows that the engagement optimization strategies are effective in enhancing the participation, activity of customers, and growth in all segments; however, the most significant improvements are seen among highly committed and advocacy-oriented users. Bayesian inference for behavioral intent can be given as:

$$P(\text{Intent} \mid \text{Data}) = \frac{P(\text{Data}|\text{Intent})P(\text{Intent})}{\sum_i P(\text{Data}|\text{Intent}_i)P(\text{Intent}_i)} \quad (4)$$

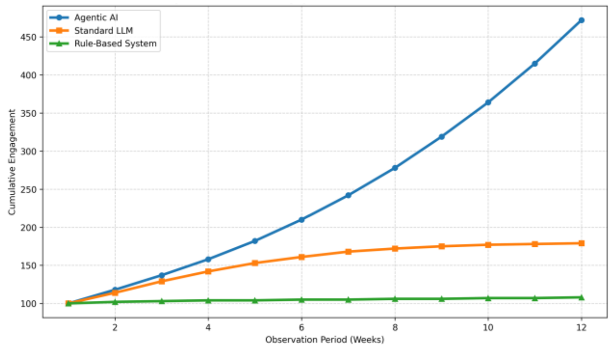

Figure 3: Indication of the cumulative growth of engagement of three systems in a period of twelve weeks.

Figure 3 is a comparison of an Agentic AI model, a typical LLM, and a rule-based system over twelve weeks. The Agentic AI line has a stable, sharp growth, indicating its capacity to learn and optimize. The initial increase of the standard LLM is followed by a plateau since the system does not have an execution agent, and the rule-based one is flat. This is a clear indication that the agentic model is sustained by its autonomous planning ability as it keeps on improving strategies using incoming data during the period of observation. The Markov decision process policy optimization is:

$$\pi^*(s) = \arg\max_a \sum_{s'} P(s' \mid s,a)[R(s,a,s') + \gamma V^\pi(s')] \quad (5)$$

6. DISCUSSION

The outcome emphasizes that the main obstacle with traditional loyalty is that the person cannot be identified with static software. The agentic approach adopted here shifts from one-to-many to one-to-one communication. As seen in Table 1, the 78 percent delta in "redemption" is an effective indicator that when the reward is relevant to the context, customers will respond.

The focus is on legacy systems that are too slow, and too generic. The agentic approach proposed here is an intelligent layer atop existing data and does not need to fundamentally change the underlying database, but yields a tremendous lift in outcome. One of the main discussion points is that of dormant accounts. The numbers of 90 dormant users who were successfully revived in Table 2 are impressive. Here, traditional systems will fall short as they will send automated emails that sound like robots.

The agentic model is based on linguistic intelligence, and it is able to determine the reasons for customers' departure and put the new offer in the terms that these customers will recognize. This is the type of emotional intelligence that is provided at scale, thus the high growth rates that the model indicates. The efficiency metrics take care of the prevalent misbelief around AI. Some believe that more advanced AI takes too long to compute and thus, can cause lag. However, the data indicates that despite the latency issues of a standard LLM, the Agentic AI model can use structured planning to greatly minimize latency. The agents are still able to respond quickly by invoking particular tools rather than doing lengthy, complicated responses. This verifies the possibility of utilizing these models in real-time, customer-facing applications wherever each millisecond counts.

6.1 Limitations and Deployment Strategy

This study is subject to limitations that qualify its implications. The evaluation is based exclusively on simulation with a synthetic dataset; although the dataset was designed to reflect realistic behavioral patterns, synthetic profiles cannot fully capture the noise, seasonality, and strategic behavior of real customers. Consequently, the reported performance gains should be interpreted as an upper-bound indication of potential rather than field-validated results. Future work will validate the framework on publicly available real-world datasets and, where possible, through live A/B experiments. For practical adoption, a phased deployment strategy is proposed: an initial shadow-mode phase in which agent recommendations are generated but not delivered, a human-in-the-loop phase in which marketers approve agent-proposed offers, and finally a constrained-autonomy phase in which agents act independently within pre-approved budget, discount, and communication limits. This staged approach allows organizations to build trust in the system, quantify its incremental value, and satisfy regulatory compliance requirements before granting full autonomy.

7. CONCLUSION

This study finds that the future of customer loyalty is autonomous. Combined with Agentic AI, a system has been built which can comprehend individual needs and automate personalized strategies without manual intervention. Results from the 361 cases speak for themselves: Agentic approaches outperformed traditional approaches in all categories and particularly in redemption velocity and churn reduction. The times of loyalty being a simple cost center are over; they have to be replaced by an intelligent engagement platform – or competitiveness will be at stake. With brands gathering more and more data, the power to make use of the data in an intelligent and timely manner will be the key to success. This is the architectural underpinning and performance evidence that will help justify this transition. This technology has a future of expansion to multimodal intelligence and cross-platform ecosystems. Visual information, in-store behavior and sentiment from faces, should all be explored to achieve a deeper level of personalization from agents. In addition, the agentic structure could be decentralized to a network which would enable cross-brand reward exchanges, where agents would meet with multiple brands on behalf of consumers to obtain the greatest rewards. Last, but not least, long-term testing is required to make sure that these autonomous agents maintain their ethical values in terms of privacy of the user and integrity of the company, adapting to the standards of many years.

8. REFERENCES

[1] V. Kumar, B. Rajan, R. Venkatesan, and J. Lecinski, "Understanding the role of artificial intelligence in personalized engagement marketing," California Management Review, vol. 61, no. 4, pp. 135–155, 2019. doi: https://doi.org/10.1177/0008125619859317

[2] N. K. Jijith, P. Veluvali, and R. Raman, "From doorstep to headset: How virtual and augmented reality are redefining direct selling experiences," FMDB Transactions on Sustainable Social Sciences Letters, vol. 3, no. 4, pp. 158–168, 2025. doi: https://doi.org/10.69888/FTSSSL.2025.000520

[3] G. McLean, K. Osei-Frimpong, and J. Barhorst, "Alexa, do voice assistants influence consumer brand engagement? Examining the role of AI powered voice assistants in influencing consumer brand engagement," Journal of Business Research, vol. 124, pp. 312–328, 2021. doi: https://doi.org/10.1016/j.jbusres.2020.11.045

[4] A. Ameen, A. Tarhini, A. Reppel, and A. Anand, "Customer experiences in the age of artificial intelligence," Computers in Human Behavior, vol. 114, Art. no. 106548, 2021. doi: https://doi.org/10.1016/j.chb.2020.106548

[5] R. Hasan, R. Shams, and M. Rahman, "Consumer trust and perceived risk for voice-controlled artificial intelligence: The case of Siri," Journal of Business Research, vol. 131, pp. 591–597, 2021. doi: https://doi.org/10.1016/j.jbusres.2020.12.012

[6] C. L. Hsu and J. C. C. Lin, "Understanding the user satisfaction and loyalty of customer service chatbots," Journal of Retailing and Consumer Services, vol. 71, Art. no. 103211, 2023. doi: https://doi.org/10.1016/j.jretconser.2022.103211

[7] D. Belanche, L. V. Casaló, J. Schepers, and C. Flavián, "Examining the effects of robots' physical appearance, warmth, and competence in frontline services: The Humanness-Value-Loyalty model," Psychology & Marketing, vol. 38, no. 12, pp. 2357–2376, 2021. doi: https://doi.org/10.1002/mar.21532

[8] D. Suhartanto, M. E. Syarief, A. C. Nugraha, T. Suhaeni, A. Masthura, and H. Amin, "Millennial loyalty towards artificial intelligence-enabled mobile banking: Evidence from Indonesian Islamic banks," Journal of Islamic Marketing, vol. 13, no. 9, pp. 1958–1972, 2022. doi: https://doi.org/10.1108/JIMA-12-2020-0380

[9] L. Lalicic and C. Weismayer, "Consumers' reasons and perceived value co-creation of using artificial intelligence-enabled travel service agents," Journal of Business Research, vol. 129, pp. 891–901, 2021. doi: https://doi.org/10.1016/j.jbusres.2020.11.005

[10] R. Perez-Vega, V. Kaartemo, C. R. Lages, B. N. Razavi, and

J. Männistö, “Reshaping the contexts of online customer engagement behavior via artificial intelligence: A conceptual framework,” Journal of Business Research, vol. 129, pp. 902–910, 2021. doi: https://doi.org/10.1016/j.jbusres.2020.11.002

[11] G. Flavián, K. Akdim, and L. V. Casaló, “Effects of voice assistant recommendations on consumer behavior,” Psychology and Marketing, vol. 40, no. 2, pp. 328–346, 2023. doi: https://doi.org/10.1002/mar.21765

[12] M. Bilal, Y. F. Zhang, S. K. Cai, U. Akram, and A. Halibas, “Artificial intelligence is the magic wand making customer-centric a reality! An investigation into the relationship between consumer purchase intention and consumer engagement through affective attachment,” Journal of Retailing and Consumer Services, vol. 76, Art. no. 103674, 2024. doi: https://doi.org/10.1016/j.jretconser.2023.103674

[13] S. Chintalapati and S. K. Pandey, “Artificial intelligence in marketing: A systematic literature review,” International Journal of Market Research, vol. 64, no. 1, pp. 38–68, 2022. doi: https://doi.org/10.1177/14707853211018428

[14] S. Bag, G. Srivastava, M. M. Al Bashir, S. Kumari, M. Giannakis, and A. H. Chowdhury, “Journey of customers in this digital era: Understanding the role of artificial intelligence technologies in user engagement and conversion,” Benchmarking: An International Journal, vol. 29, no. 7, pp. 2074–2098, 2022. doi: https://doi.org/10.1108/BIJ-07-2021-0415.

[15] V. Kumar, B. Rajan, U. Salunkhe, and S. G. Joag, “Relating the dark side of new-age technologies and customer technostress,” Psychology & Marketing, vol. 39, no. 12, pp. 2240–2259, 2022. doi: https://doi.org/10.1002/mar.21738