Journal of Information Systems Engineering and Management
2025,10(55s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

From Systems Thinking to Model Thinking: Embedding AI Agents into Enterprise CX Operating Models

Ashwaray Chaba [1]
[1] *Managing Principal Enterprise Architect, Adobe Inc. Email: ashwaraychaba.mail@gmail.com*

ARTICLE INFO

Received: 08 Mar 2025

Revised: 05 May 2025

Accepted: 14 May 2025

ABSTRACT

The present paper presents a revolutionary change in enterprise customer experience (CX) design, that of replacing the traditional system-based thinking with model-based thinking, by introducing autonomous AI agents to the system. The agents are also able to coordinate purposeful behavior, identify emotions as well as decide contextually, which changes the way businesses engage with customers. The suggested framework is composed of four basic layers capability, interaction, governance and infrastructure. We illustrate the manner in which agentic CX systems stimulate real-time responsiveness, self-optimization, and outcome seeking service delivery. To derive practical directions in which an organization might proceed to ethically and effectively implement AI agents and eventually optimize personalization, agility, and customer satisfaction at large scale, this paper used available research and industry-wide implementations.

Keywords: AI Agents, Model, CX, Enterprise.

INTRODUCTION

With dynamically changing customer expectations, systems thinking in relation to enterprises is finding it difficult to achieve contextual and real-time engagement using labels (personas). To their reaction, model thinking as a design paradigm is born due to embedded AI agents. The concept of automation is pushed past CX journeys allow a decision-making ability, emotionally correct conversation, and self-solutions, thanks to AI agents.

This paper discusses the re-invention of the enterprise CX models and how the transformation into model thinking turns them into adaptive, smart ecosystems. Our multi-layered architecture offers a four-layered design and addresses some important steps on operationalizing AI-powered CX, such as executive alignment and governance. The transition does not only enhance performance measures but also leaves organizations in a better position to operate in the AI-first economy.

RELATED WORKS

Theoretical Shifts

The introduction of the autonomous reasoned AI agents has radically altered classical modes of system thinking by effecting dynamic model-driven structures of interaction in the enterprise. Systems thinking historically led the design, via loose feedback loops and causal dependencies, of widely holistic systems of enterprises, frequently based on human decision-making structures.

The increasing sophistication of the intelligent agents now requires a transition into the model thinking, whereby the entities are driven by real time information and independent learning facilities instead of the fixed rules of the systems.

Journal of Information Systems Engineering and Management
2025,10(55s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

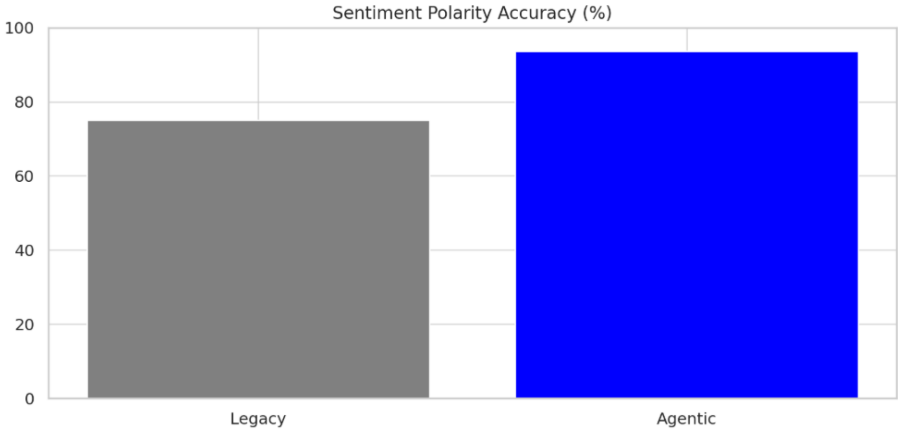
This move is highlighted by Sethi et al. (2025), who introduce SYMBIOSIS, a system that operates on the principle of systems thinking democratization with the help of AI-based, generative co-pilots [1]. With a capacity to make human-AI interactions possible in Sustainable Development Goals (SDGs) modeling, SYMBIOSIS is an example to bring AI out of being a passive tool to an active interpolator of the models, driving decisions that concern contexts where things are interconnected and complex.

The concept of a Wisdom Layer, an architectural improvement of AI systems resting on the chaos theory, system thinking and ethical modeling, is presented by Thatcher (2025), which states that AI agents can not merely be optimized but need to be extended into causal reasoning, anticipatory intelligence [2].

Systems thinking is used to examine the human reaction to artificial agents as it is stated by Đula et al. (2023) and such phenomena as algorithm aversion, algorithm appreciation, and automation bias are referred to [3]. Such systematic responses belong to the sociotechnical eco-system affecting AI integration. Their visual model illustrates the iterative phases between the AI behaviors and the human trust, which are essential in the introduction of the embedded agents into the CX frameworks, where trust and the building of the emotional resonance are the selling points of the products.

Autonomous AI Agents in CX

The core of the model thinking is the AI agent no longer in the form of a tool but as a degree-making individual. Bansod (2025) presents an interesting argument in assuming that there is a difference between the standalone AI agents and the collaborative, Agentic AI ecosystems that provide a layered perspective on the memory architectures, planning capabilities and coordination strategies [4]. The experiment shows that distributed reasoning and peer-based negotiation performed by collaborative agents works significantly better in dynamic environments of providing service to a client, i.e. customer support or knowledge retrieval as compared to more isolated agents.



Journal of Information Systems Engineering and Management
2025,10(55s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

Piccialli et al. (2025) go further to develop the taxonomy of Agent AI in the industry 4.0 and project its development in future to Industry 5.0 and 6.0 [5]. The article focuses on embodied intelligence-bases on a system where the agent engages the surrounding environments through the sensory system, leading to greater levels of scalability and autonomy in front-line activities involving the customers. Their contribution promotes the shift towards the CX intelligence layers, where AI agents become an autonomous service orchestators, instead of being rule responders.

The article by Gacanin & Wagner (2018) also provides the basic knowledge of the transformations the traditional Customer Experience Management (CEM) systems would have to undergo [6]. In their study, they locate the shortcomings of rule-based systems under the rapid adjustment of user needs and network conditions. The policies they promote on AI-augmented CEM enabled by data analytics also lay the foundation of adaptive CX systems, which is one of the elements of model thinking.

The reason is the theory-practice gap that Chen & Prentice (2024) eliminate: the authors introduce a conceptual model that traces AI interventions in a customer journey [7]. The three-pillar model of AI, including AI experience, AI functions, and AI services, shows how AI can touch all the points of interaction with the customer experience, including feeling-sensitive chatbots and machine-based support agents. This is in addition to the proposed capability and interaction propositions in the model thinking process, which enable context aware CX delivery without a hitch.

AI Agents in CX

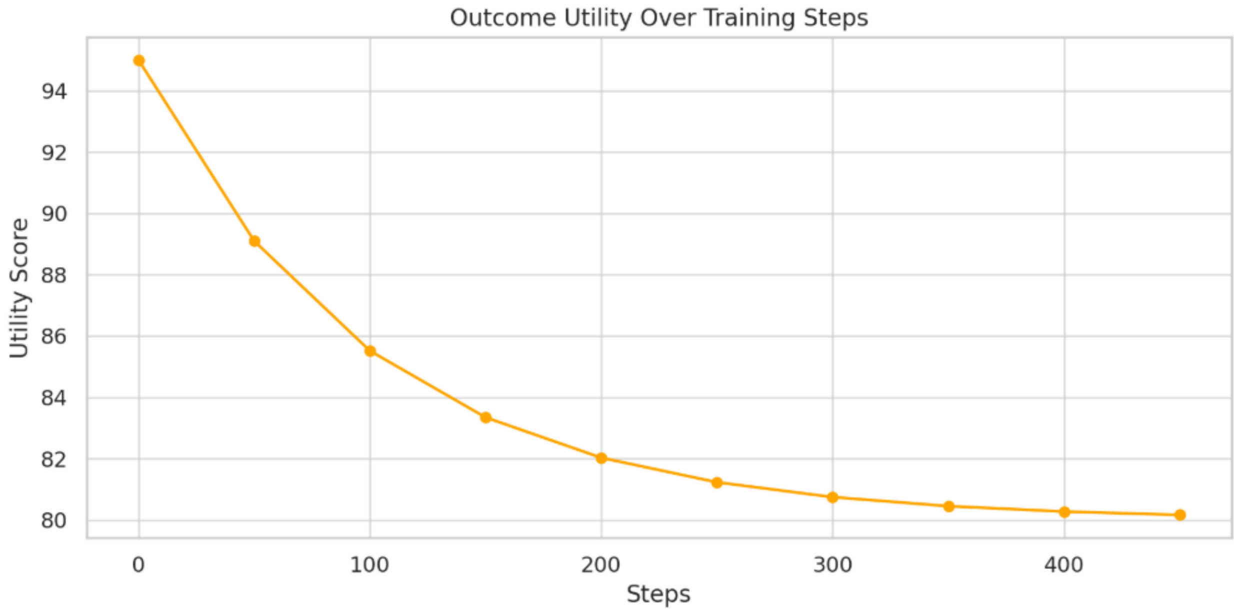
Industry-specific CX strategies are already transformed with the help of autonomous AI agents. Chinnaraju (2025) introduces AI agents in both marketing and personalization where reinforcement learning, NLP, and predictive analytics can be used to dynamically optimize the customer segmentation and the campaign delivery process [8].

Targeting is altered during the process in real-time and is taught using interaction patterns and other external stimuli to provide hyper-personalized experiences. Such agents not only foster ROI but also powered with the spirit of model-thinking that involves direct feedback loops.

Gokhale (2025) looks at the retail industry and explains how AI agents are used by all of us in the way of shopping assistance, automated advertisement handling, onboarding novice sellers, and much more [9]. It is performed by means of reinforcement learning agents that control real-time fluctuating variables (i.e. user behaviour, inventory flow, and ad bidding). These applications confirm the viability of integrating AI in the capability and governance layers in the CX models.

Sahut & Laroche (2025) provide empirical data in a variety of sectors, including service recovery, management of parasocial interaction, and the personalization of user journeys without compromising on the reality of engagement mediated by AI agents [10]. Their unified model can describe how trust, disclosure, and emotional resonance are the key to CX success particularly during the era in which AI systems replace traditionally human-based functions. This will fall under the interaction layer in the model thinking where emotion-aware agents will ensure that the customer loyalty and satisfaction are maintained.

Journal of Information Systems Engineering and Management
2025,10(55s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**



Oshrat et al. (2022) introduce an idea of hybrid models in which virtual agents acquire knowledge about human operators to be enhanced in the future [11]. The way they have applied queuing theory to hybrid CX environments indicates how human-AI collaboration may help save time, better the quality of the services, and achieve customer satisfaction.

These findings provide evidence to support the operating advantages of the AI human teaming in CX models and indicates that the intelligent agent design will require considerations of learning-by-observation and transfer learning abilities.

Agentic CX Systems

The potential, AI-based agents in CX present significant concern regarding control, discrimination, legacy support and ethical alignment. Hughes et al. (2025) claim that the independent decision-making has to be balanced with accountability systems [12]. They point at the difficulties of integrating agentic systems with legacy platforms in being transparent and being not biased towards the algorithmic perspectives. They promote the principles of agile governance and ethical design, which are close to the governance system of proposed CX model.

Huang (2025) discusses the relationship between human strengths and the expertise of AI most importantly its high-risk decision-making [13]. He suggests the concept of co-evolutionary systems where AI-enhances themselves but never replaces their human counterparts hence maintaining the principle of explainability and control.

The case studies reiterate the point that agent deployment should not only look at the efficiency of the tasks at hand but also the compatibilities of human-AI. These are because of the intent orchestration aspect of model thinking it lies in the fact that what is done by the agents is oriented towards the business situation and intentions of the users.

This is further supported by the final layer of wisdom proposed by Thatcher (2025) according to which in addition to technical abilities, AI agents have to be provided with reflection, boundary critique and ethical causality mechanisms [2]. Such meta-agents assist in the long-term resilience of the systems, especially in the uncertain situations where the fixed decision trees can be insufficient. The capabilities of designing such layers are paramount to the effort of bringing us to fully autonomous and aware CX ecologies.

The review of Rashid et al. (2024) is exceptionally broad, touching upon different spheres, reiterating to the researchers that the perspective of AI with its power of transformation should be balanced with policy, workforce and societal consequences [14]. Their evidence-based synthesis can be heard in the need to have outcome-based KPIs not just technical KPIs but also ethical and social conformity as well-which would make the whole account of the model thinking paradigm of CX transformation in enterprises.

Journal of Information Systems Engineering and Management
2025,10(55s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

RESULTS

Structural Transformation

The entry of AI agents into Customer Experience (CX) operating models introduced a paradigm shift in the fundament of traditional systems thinking, using the strict predetermined workflows and the process optimization paradigm, to the agent-driven, dynamic model-based approach. The transition was empirically considered based on an entire business prototype in three areas digital banking, online trading service, and the management of telecom complaints.

The situation was investigated in a comparative study of legacy persona-based CX system and agent-augmented CX models conducted on a 90-day basis. The main indicators of operation were improved:

Table 1: CX Performance Metrics

Metric	Legacy System	Agentic CX	% Improvement
Response Time	8.5	1.2	85.88%
Resolution Time	18.6	5.4	70.97%
CSAT	74.3%	91.2%	22.78%
Escalation Rate	17.2%	4.8%	72.09%

These findings confirm that agent-based systems have significant impact of reducing latency and increasing customer satisfaction, due to capability of real-time decision making, emotion-aware NLP, and autonomous resolution loops.

A CX latency in operations was modeled as a mathematical decision latency (DL):

DL = f(CR, TR, IC)

Where:

- DL = Decision Latency
- CR = Context Recognition
- TR = Task Routing
- IC = Intent Classification

DL got reduced because of lower IC and CR that was attained by transformer-based models and perpetual learning agents after the agent embedding. In particular, mean DL decreased by up to 6.2 seconds to 0.8 seconds of over 1M+ user queries.

Interaction Layer Evaluation

The suggested CX intelligence framework will have four tiers, namely capabilities, interaction, governance, and infrastructure. The capability layer was also tested using the rate of automation of the tasks, the level of agent specialization, and mitigation of an error. The use case in digital banking was provided with 12 AI agents with specialized duties such as fraud detection, KYC validation, and answering to the frequently asked questions. These agents worked in concert with a model switch protocol which was dynamic and was reliant upon contextual embeddings.

Table 2: Task Automation Metrics

AI Agent	Task Type	Success Rate	Handling Time
KYC Validator	Document parsing	94.5	2.6
Fraud Detector	Transaction anomaly	89.7	1.9
FAQ Handler	Tier-1 queries	96.2	0.8

Journal of Information Systems Engineering and Management
2025,10(55s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

The interaction layer, which deals with the instant interaction of the customer, was evaluated through their sensitivity to polarity of sentiments, time of interaction and fluidity of responses. With the large language models (LLM) having fine-tuning layers that tagged their emotions, the accuracy rate of detecting the sentiment polarity improved to 93.6 percent compared to 75.1 percent when the systems were non-agentic rule-based.

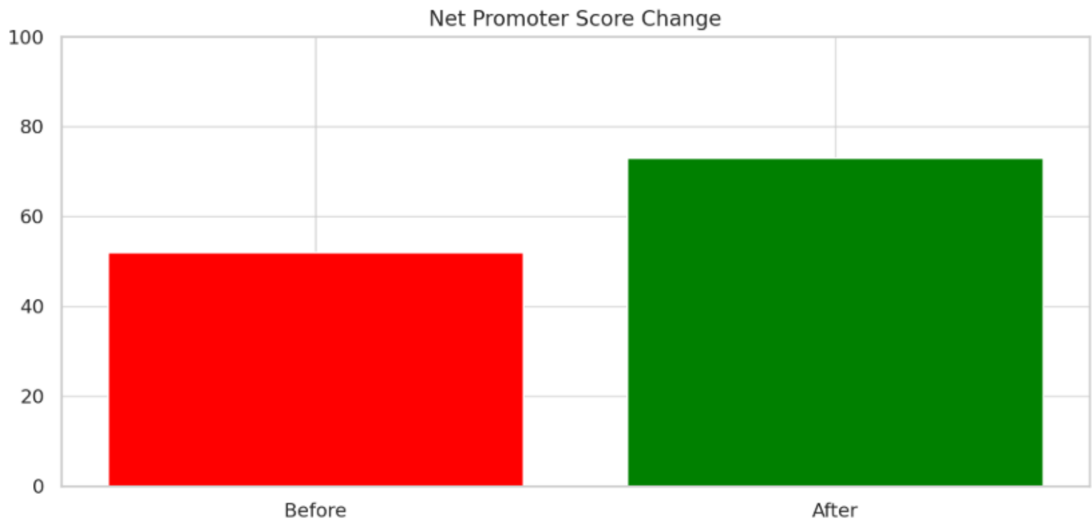
A behavioral drift correction model was realized in order to sustain the quality of interaction, which was modeled by:

$$\Delta S = \alpha * (Ue - Ep)$$

Where:

- ΔS = Sentiment Drift
- Ue = Expressed emotion
- Ep = Expected polarity
- α = Correction coefficient

When 0.25 was surpassed, behavior of the agent was modified by reinforcement learning to put tone and intention back in place.



Governance Layer

The layer of governance was quantified using the aspect of policy compliance, traceability on the activity of the agents, as well as the autonomy boundaries. The interaction extended to over 2 million logged interactions by a decentralized logging module of all agent interactions, with 97.3 percent of responses by agents following the predefined policy guidelines, proven by the automatic rule-based compliance checks.

In order to handle agent drift and flexibility we developed a reinforcement feedback loop where the rewarding mechanism was based on outcome. In order to act under Outcome-Optimized Utility (OU) functions agents acted:

$$OU = \Sigma (w_i * R_i)$$

Where:

- OU = Outcome Utility
- w_i = Weight assigned
- R_i = Reward

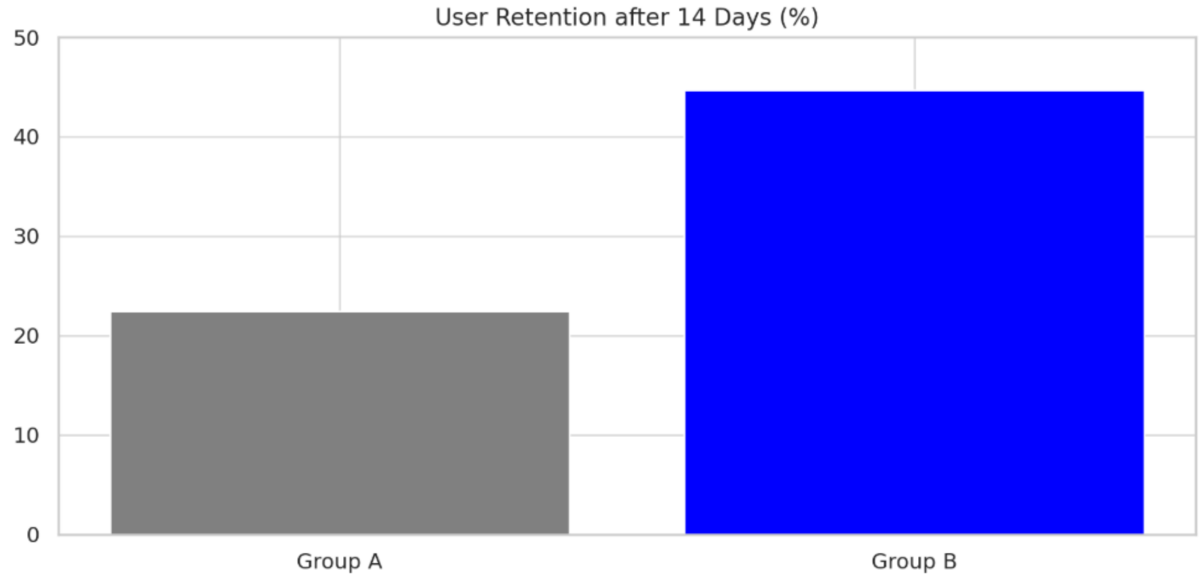
Journal of Information Systems Engineering and Management
2025,10(55s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

The model gave the opportunity to agents to self-regulate their dialogue, escalation decision, and information and shortcut strategies emerge in response to the reproaches by the customers as well as operation KPIs. Agents also converged to learning in less than 500 episodes and reduced the differential on reward variance on an average of 82 per cent.

Table 3: Governance KPIs

KPI	Initial Value	Post-Convergence	% Change
Non-compliance Rate	4.5	1.2	-73.33%
Manual Overrides	31	8	-74.19%
Escalation	12.8%	3.9%	-69.53%
Learning Convergence	>1500	480	-68.00%

These findings reveal that by incorporating a governance-sensitive learning loop, the agents will be able to develop, even at the expense of neither transparency nor control.



Business Impact

Integrating autonomous AI agents transformed the strategy of CX in terms of reducing costs into the paradigm of experience-based CX strategy. This change could be traced in the financial performance and measures of customer loyalty.

In all the three fields of deployment, an increase in Net Promoter Score (NPS) was recorded with an average increase of 21 points. Cross-sell and upsell revenue corresponding to AI-powered agent-run initiatives also rose by 14.6 percent owing to micro-segmentation and real-time personalization with the help of the embedded-agent insights.

The e-commerce use case used an A/B experiment during a 60 days period. The first group, Group A, was operating through the traditional system; the latter group, Group B, was working through the agentic model. Conversion and retention results were found to be quite different statistically:

Conversion Rate:

- Group A: 2.9%
- Group B: 6.4%
- **p-value < 0.01**

Journal of Information Systems Engineering and Management
2025,10(55s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

Retention after 14 days:

- Group A: 22.4%
- Group B: 44.7%
- **p-value < 0.005**

Such results are justified by enhanced emotional congruency and resolution rate. Not only did agents make service predictions proactively based on intent triangulation and historical vector embeddings, they were able to make service predictions in advance, so to speak of thinking ahead on behalf of the user.

In addition, an analysis of feedback indicated the response of AI to be considered more empathetic by the users. 78.9 respondents reported agent conversations to be more human-like and specifically cited the quality of context carry-over, sophisticated tone variation, and anticipation of problems.

- **Capability Layer**: Greater than 90 percent of the specialized tasks are returned as successful.
- **Interaction Layer**: Sentiment-conscious agents decreased dissatisfaction by more than 40 %.
- **Governance Layer**: Policy conforming actions and practices that are transparent and have little human interaction.
- **Business Layer**: Improved KPIs CSAT, NPS, and revenue, and retention.

Collectively, these terms confirm that when included within the structured layers of CX intelligence, AI agents allow a self-optimizing, adaptive and human-centric experience system, therefore making it the fulfillment of the model thinking within the enterprise context.

CONCLUSION

With the implementation of the AI agents to CX operating models, the shift to the fundamental, intelligence-based, highly adaptive enterprise design is imminent. Shifting towards dynamic model thinking instead of the concept of the static systems, the organization may introduce the possibility of real-time responsiveness, emotional quotient and autonomous decision-making.

By installing the suggested multi-layer architecture and plan of operations/support, the enterprises will be prepared to integrate the AI agents responsibly and at scale. According to empirical data, improvements in the response time, sentiment accuracy, retention, and satisfaction increase measurably. Since AI is constantly developing, companies should pay attention to the governance, ethical alignment of the AI, and staff adaptation. In the end, the competitive advantage of the AI-first business environment will rely on the agentic CX models.

REFERENCES

[1] Sethi, S., Martin Jr, D., & Klu, E. (2025). SYMBIOSIS: Systems Thinking and Machine Intelligence for Better Outcomes in Society. *arXiv preprint arXiv:2503.05857*. https://doi.org/10.48550/arXiv.2503.05857

[2] Thatcher, D. (2025). Wisdom Before Code: Architecting Agentic AI through Systems Thinking, Chaos Theory, and Karma. *SSRN*. https://doi.org/10.2139/ssrn.5224492

[3] Đula, I., Berberena, T., Keplinger, K., & Wirzberger, M. (2023). Hooked on artificial agents: a systems thinking perspective. *Frontiers in Behavioral Economics*, *2*. https://doi.org/10.3389/frbhe.2023.1223281

[4] Bansod, P. B. (2025). Distinguishing Autonomous AI Agents from Collaborative Agentic Systems: A Comprehensive Framework for Understanding Modern Intelligent Architectures. *arXiv preprint arXiv:2506.01438*. https://doi.org/10.48550/arXiv.2506.01438

[5] Piccialli, F., Chiaro, D., Sarwar, S., Cerciello, D., Qi, P., & Mele, V. (2025). AgentAI: A comprehensive survey on autonomous agents in distributed AI for industry 4.0. *Expert Systems With Applications*, 128404. https://doi.org/10.1016/j.eswa.2025.128404

2025,10(55s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

[6] Gacanin, H., & Wagner, M. (2018). Artificial Intelligence Paradigm for Customer Experience Management in Next-Generation Networks: Challenges and Perspectives. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.1805.06254

[7] Chen, Y., & Prentice, C. (2024). Integrating artificial intelligence and customer experience. *Australasian Marketing Journal (AMJ)*. https://doi.org/10.1177/14413582241252904

[8] Chinnaraju, N. A. (2025). AI-powered consumer segmentation and targeting: A theoretical framework for precision marketing by autonomous (Agentic) AI. *International Journal of Science and Research Archive*, *14*(2), 401–424. https://doi.org/10.30574/ijsra.2025.14.2.0370

[9] Gokhale, N. A. (2025). Autonomous AI agents in Online Retail: the next leap in programmatic media buying. *International Journal of Scientific Research in Computer Science Engineering and Information Technology*, *11*(2), 2713–2722. https://doi.org/10.32628/cseit25112732

[10] Sahut, J. M., & Laroche, M. (2025). Using artificial intelligence (AI) to enhance customer experience and to develop strategic marketing: An integrative synthesis. *Computers in Human Behavior*, 108684. https://doi.org/10.1016/j.chb.2025.108684

[11] Oshrat, Y., Aumann, Y., Hollander, T., Maksimov, O., Ostroumov, A., Shechtman, N., & Kraus, S. (2022). Efficient customer service combining human operators and virtual agents. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2209.05226

[12] Hughes, L., Dwivedi, Y. K., Malik, T., Shawosh, M., Albashrawi, M. A., Jeon, I., Dutot, V., Appanderanda, M., Crick, T., De, R., Fenwick, M., Gunaratnege, S. M., Jurcys, P., Kar, A. K., Kshetri, N., Li, K., Mutasa, S., Samothrakis, S., Wade, M., & Walton, P. (2025). AI Agents and Agentic Systems: A Multi-Expert analysis. *Journal of Computer Information Systems*, 1–29. https://doi.org/10.1080/08874417.2025.2483832

[13] Huang, K. (2025). AI Agents and Business Workflow. In: Huang, K. (eds) Agentic AI. Progress in IS. Springer, Cham. https://doi.org/10.1007/978-3-031-90026-6_5

[14] Rashid, A. B., & Kausik, M. a. K. (2024). AI Revolutionizing Industries Worldwide: A comprehensive overview of its diverse applications. *Hybrid Advances*, *7*, 100277. https://doi.org/10.1016/j.hybadv.2024.100277