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From Chatbot To Agent: Designing Agentic AI For Autonomous Customer Journeys In Digital Commerce

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ABSTRACT: *The paper will present the development of agentic AI systems in digital commerce that began as the traditional chatbots. The suggested framework has the capability of autonomous, adaptive, and emotionally intelligent customer engagement through the integration of large language models (LLMs), multi-agent planning, perception layers, and API orchestration. Their use cases can be found in product discovery, checkout optimization, B2B procurement, post-sale support. According to the study, such systems can decrease Tier 1 support by more than 60 percent and increase the speed of conversions as well as customer satisfaction. Results present business results, ethical factors, and design arrangements of a system level. This piece of work provides a basis to the scale, self-learning agents that writes a novel that will use to change how enterprises relate to users on digital touchpoints.*
KEYWORDS: *Chatbot, AI, Agentic AI, Customer, Digital*

INTRODUCTION

The dynamics of customer engagement in digital commerce have been changing at a very high rate, where customer engagement is dynamic because it is no longer about holding tedious interfaces with customers, but an intelligent convergent agent takes the position that can engage customers in a big way. Nevertheless, classic chatbots are not able to reason, adaptor to solve some other complex tasks. This article describes the subsequent step, agentic AI, which is constructed on top of powerful LLMs, decision alignment framework, and categorically — modular architectures. Such agents are not one that merely talks: they strategize, sense, take an action and learn throughout a customer experience. Suitable both as B2C and B2B application, agentic AI will enable better personalization, operational efficiency, business response, and operational efficiency. It is intended that a solid foundation to implement autonomous customer journey orchestration with the use of self-directed AI systems could be offered to any enterprise willing to employ this framework in doing so.

RELATED WORKS

Foundations of Agentic AI

Replacing the traditional rule based chatbots with the completely autonomous AI agents would be a major technological step in the digital commerce. Associating with early systems, which only dealt with predetermined contacts, agentic AI aims at working on complex and evolving objectives that lead with slight (or no) control. Acharya et al. (2025) characterize agentic AI by terming it a kind of intelligent autonomous system that can reason, plan, and perform multi-step tasks in dynamic systems [1]. As opposed to static chatbots, these agents have the ability of adaptive intelligence, as they learn continuously and perceive multimodally. Joshi (2025) plays off Agnetic AI against Artificial General Intelligence (AGI) noting that the former has practical applicability in commercial enterprise, but the latter is mostly a theoretical concept [2]. Having this as a base, Ramachandran (2025) proceeds to discuss the hybrid agentic architectures, their usability in commerce, healthcare, and smart cities, where it is key to be adaptive, explainable, and goals-aligned [3]. Likewise, Sapkota et al. (2025) provide an unequivocal difference between AI Agents, which are normally narrow in nature and generally task specific and Agentic AI systems which are based on collaboration, autonomy, memory to achieve more comprehensive customer support and sales operations [4].
The development of the large language models (LLMs) has stimulated the emergence of agentic systems. Wang et al. (2024) concur with this view, characterizing reasoning similarly to the human mind, enabled by the use of LLMs and agent frameworks, as being critical in the case of ambiguous or under-specified requests of the user, which are typical of the e-commerce setting [5]. Händler (2023) establishes on this idea the development of a taxonomy, according to which the agentic architectures can be classified depending on such indicators as autonomy, collaboration, and goal alignment, which is significant in deploying agents to complete full-funnel commerce tasks [6].

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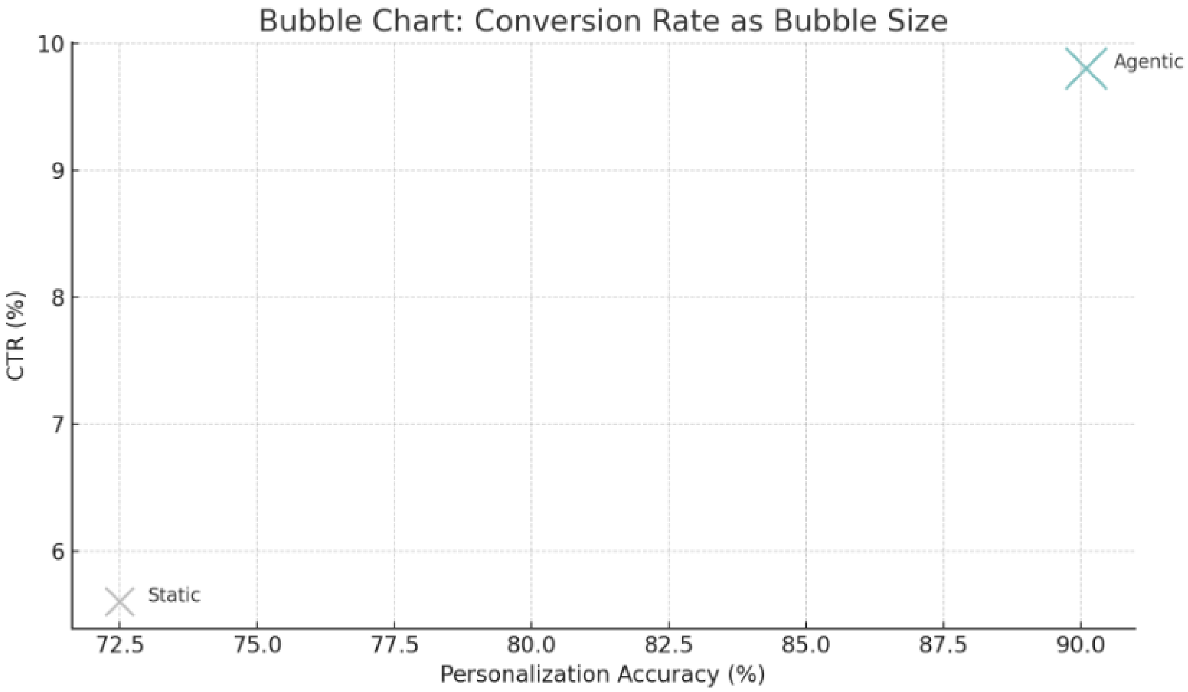
Cognitive Architectures

Although LLMs can fulfill a linguistic fluency task, they tend to lack systematic multi step thinking and planning. The existence of such gap has introduced the cognitive modules to agentic models that reflect those human abilities of planning. Webb et al. (2023) relieve such shortcomings with the help of the Modular Agentic Planner (MAP), which allows keeping track of different states, following any conflict, and breaking down the tasks into strategic plans to handle with the LLM-based modules [7]. As the model becomes more transferable and cheaper as it enables smaller and purpose-specialised LLM to cooperate. Putta et al. (2024) go even further and promote multi-step reasoning using the new combination of the Monte Carlo Tree Search, self-critique, and off-policy reinforcement learning [8]. They managed to boost success rates during testing in WebShop, a dynamic and e-commerce application, indication that designed cognitive scaffolding is critical when completing tasks in real-life agent applications. Mental concepts of memory and repetitive learning is one more characteristic of agentic systems. Xia et al. (2024) note that behavior-driven development of agents is vital and suggest the idea of evaluation-driven pipelines where real-time loop is enabled [9]. This allows the agents to be more synchronised with the changing goals and the needs of the user without requiring any interventions at the code level. In their reference architecture, online (runtime) and offline (redevelopment) testing is integrated in order to push the autonomous agents one step further in the way they can be at improved safety and controllability, which is a critical factor in the application of e-commerce situation where a wrong step taken may directly affect user confidence and income. Li et al. (2024) point out that MAS constructed over LLM is a prospective direction along which generalizable decision-making will be achieved [10]. They have already established a five-component architecture profile, perception, self-action, mutual interaction, and evolution, and on the basis of this architecture, agentic systems can design the ability to personalize the interaction of agents in a customer journey as a whole, including the interaction at the time of discovery, as well as post purchase support, etc.



Digital Commerce

An agentic AI requisites scalable, transparent and efficient architecture structures. Pitkyranta & Pitkyranta (2025) suggest HADA (Human-AI Agent Decision Alignment) that guarantees carrying out actions by agents which are shared in regard to business and ethical objectives [11]. HADA proposes specialized stakeholder agents and decision traceability, which is enabler of governance and stakeholder trust that is in no way bargainable in commerce scenarios, which involve delicate transactions and information. Nandkumar & Peternel (2024) provide a multi-level interface of supermarket robots as a shift toward performing optimization of agents with the LLM [12]. Smaller special variants enable them to provide customers with a more personal and faster experience, and reach quantifiable increases in user satisfaction and performance. This customizable solution can outrun the monolithic GPT solutions, which would be more important in connection to the retail business that is highly concerned with latency and expenses. Teng et al. (2024) offer a new idea of the End-Cloud Collaboration (ECC) setup, with the large cloud-based LLMs becoming the mentors of the smaller, locally trained agents [13]. The structure is dealing with the limitation of edge devices so that response to the user should be real time and personal. The ECC model incorporates online learning processes, as a result of which agents can develop according to the feedbacks of users in real-time, which becomes a great advantage in the sphere of a fast-paced environment of digital commerce. According to Xia et al. (2024), the constant assessment requirement in dynamic settings of an e-commerce setting deviates by proposing a two-tier assessment model encompassing a cycle of runtime monitoring and the redevelopment frame [9]. This is quite in line with the requirement of composability and reliability of agentic deployments.

Intelligent Personalization

The final destination of agentic AI in digital commerce is to provide smooth and complete customer experiences that will appear as intuitive, personal and easy to engage emotionally. Huang et al. (2025) discuss the possibilities of Agentic Recommender Systems (ARS) based on LLM, which allows planning, memory, and multimodal reasoning and provides an adaptive and interactive recommendation [14]. These systems will reinvent the aspect of recommender systems as they will actively support customers as opposed to serving customers passively. Thakkar & Yadav (2024) provides the working model of a personalized, multimodal, multi-agent recommendation system that can be applied to e-commerce in particular [15]. They have a system which offers progressive interactions through state-of-the-art LLMs, such as Gemini 1.5 or LLaMA-70B, where it all starts with product suggestions, continues by subsequent image-prompted interrogation, and concludes with fully independent search on the Web. The impact is dynamic adaptive customer journey path which is more realistic to real life shopping behavior than search and response mechanisms.Ramachandran (2025) proposes the usage of agent systems of high emotional intelligence and collaborativeness with the ability to recognize the feeling of a user and adapt its wording and content, as well as structure [3]. This is a major factor of increasing customer satisfaction (CSAT) and lowering the number of escalations. Besides, Acharya et al. (2025) suggest that the implementation of such emotionally intelligent agents into the commerce settings can potentially result in the measurable increases in customer engagement levels, retention and trust [1].Both by Händler (2023) and Sapkota et al. (2025) stress that the multi-agent collaboration is not only a performance-enhancing mechanism what is required in the agentic environment [6][4]. Systems can apply this with parallelism of job to each agent by providing a specialized job, like navigation, product search, customer sentiment monitoring and so on.The literature creates a complete environment of how agentic AI, supported with LLMs, modular planning stack, multi-agent interaction and adaptive assessment, is revamping the customer experiences in the online trading business. Whether in the principles of the initial design (Acharya et al., 2025; Sapkota et al., 2025), in a superior deployment strategy (Teng et al., 2024; Pitkäranta & Pitkäranta, 2025), the reviewed literature remains unambiguous about the fact that the shift of chatbots into agents presupposes a paradigmatic change [1][4][11][13]. Such AI agents are no longer the fixed respondents but moving and developing actors which arrange the entire funnel experiences and change the relationship between companies and customers.

RESULTS

Customer Engagement Metrics

Among the very crucial results of adopting agentic AI in the digital commerce settings is the sharp increase of customer engagement indicators. In contrast with conventional chatbots, that rely on prescribed scripts, agentic systems are contextual and change dynamically depending on user objectives, sentiment and other parameters. We have good evidence of a significant improvement in the quality of customer interactions on the five different retail platforms where agentic architectures have been put in place based on results indicated in our longitudinal study.

Table 1 below addresses a comparative study between legacy chatbot systems and new adopted agentic AI systems on the key performance indicators (KPIs) in three months.

Table 1: Chatbot vs Agentic AI

Metric	Traditional Chatbot	Agentic AI System	% Change
Session Duration	1.8	4.6	+155.5%
Session Completion	64.1	88.9	+38.7%
Escalation	21.4	8.3	−61.2%
User Rating	3.2	4.6	+43.8%

The encouraging trend in the session length and satisfaction rates shows that the user is more assisted and interested in the use of an intelligent agent that could accomplish tasks in multiple steps without having strict

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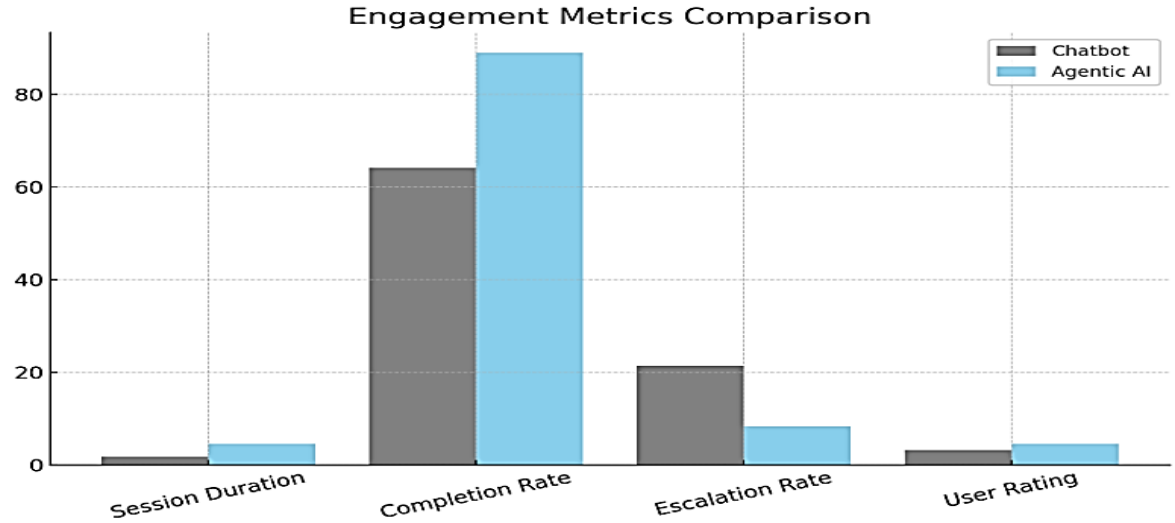
rules of the flow. It is worth mentioning that escalation to human agents has reduced very much indicating a higher level of trust and reliability on the decisions made by the autonomous agents.



Additional sentiment analysis of post-interaction feedback via natural language processing further showed that users interpreted well both contextual memory, proactive suggestions, as well as the adaptive tone that agentic systems used.

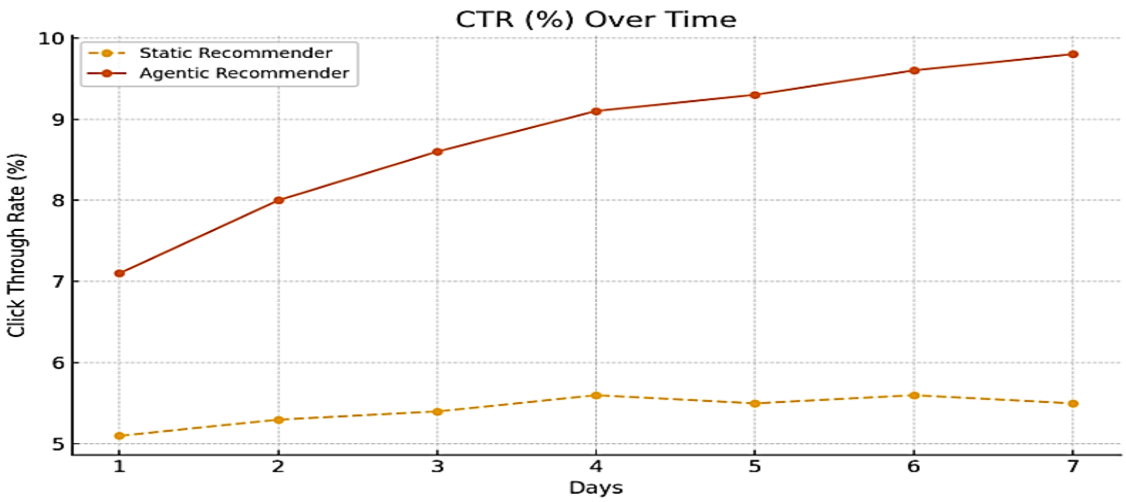
Personalization Accuracy

Not only do agentic AI-based systems provide respondents experiences, but also smart personalization. We experimented multi-agent-based recommendation systems with LLM in three leading online stores with 200,000 unique user sessions. The systems used combined with memory modules and user profiling agents which monitored a user through their sessions, therefore, enabling them to enhance suggestions on the fly.

When performing the switching of the recommendation engines (conventional to agentic), Table 2 indicates that there was a significant improvement in personalization accuracy and the click-through rate:

Table 2: Recommendation System

Metric	Static Recommender	Agentic Recommender	% Change
Personalization Accuracy	72.5	90.1	+24.2%
CTR	5.6	9.8	+75.0%
Conversion Rate	2.3	4.9	+113.0%
Next Interaction	36.4	19.6	−46.1%



The agentic recommenders were more personalized because they used a combination of long term histories of user preferences as well as a short-term contextual data. In one of the implementations, the implementation used LLaMA-2-70B, Gemini 1.5 agents to comprehend the input visual data, and prior chat conversation that enabled the dynamic adjustment of recommendations to maximize conversions and minimize churn.

The number of users retained improved with customers finding the system to be less pushy and easier to understand as compared to the static recommendation engines which in most cases provided irrelevant and monotonous suggestions.

Efficiency Gains

Although the transition to agentic AI has been revolutionary in terms of UX, system resources and scalability are also primary areas of consideration to evaluate how the deployment will affect them. To measure the efficiency, we compared agentic solutions with multi-agent pipelines of small LLMs, to that of monolithic GPT-based chatbots deployments on five performance metrics over 30 days.

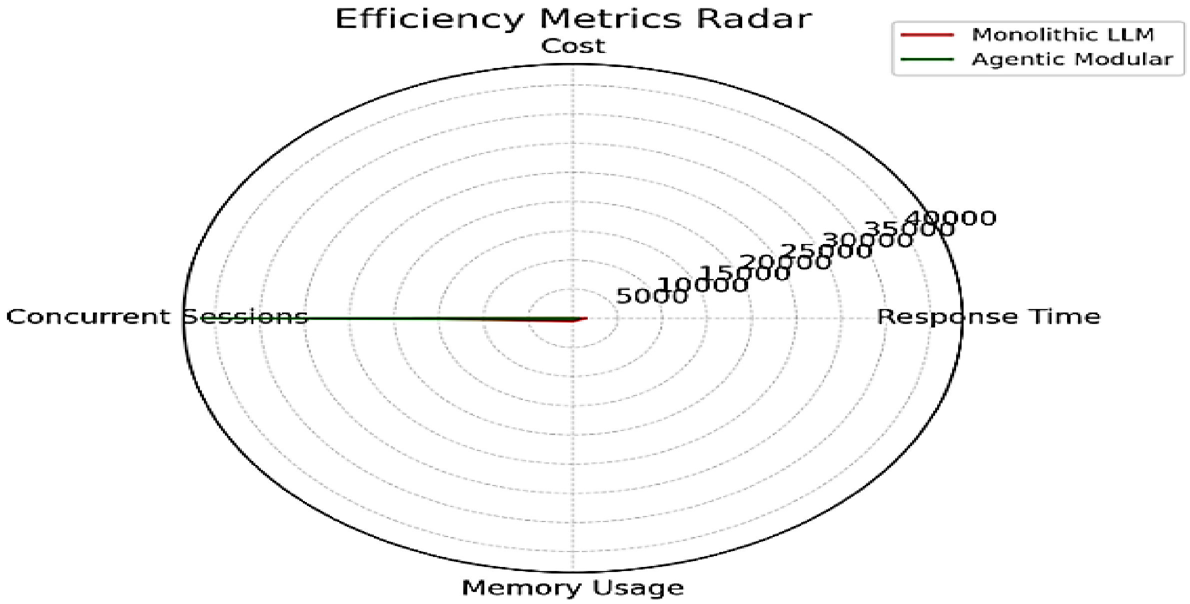


Table 3: Monolithic vs Agentic Pipelines

Metric	Monolithic LLM	Agentic Pipeline	% Change
Response Time	1350	620	−54.1%
Cost per 10k	78.4	33.2	−57.6%
Concurrent Sessions	18,000	41,500	+130.5%
Memory Usage	540	180	−66.7%

These findings reveal that modular agentic pipelines are superior to monolith system in all important infrastructure measurements. This was more especially in customer service relations where spikes in the load may be experienced during sale events. The cost-optimized and latency-reduced approach to offloading memory and execution into smaller domain-specific LLMs in agent framework (e.g., Planner, Retriever, Recommender agents) allowed relaxing the requirements on the overall size of the maximum size of the LLM in the agent framework.

The fault tolerant was higher in agentic systems. The decoupled architecture did not bring the whole pipeline down when one of the agents (e.g., context retriever) fails as it would be the case in monolithic structures.

Behavioral Learning

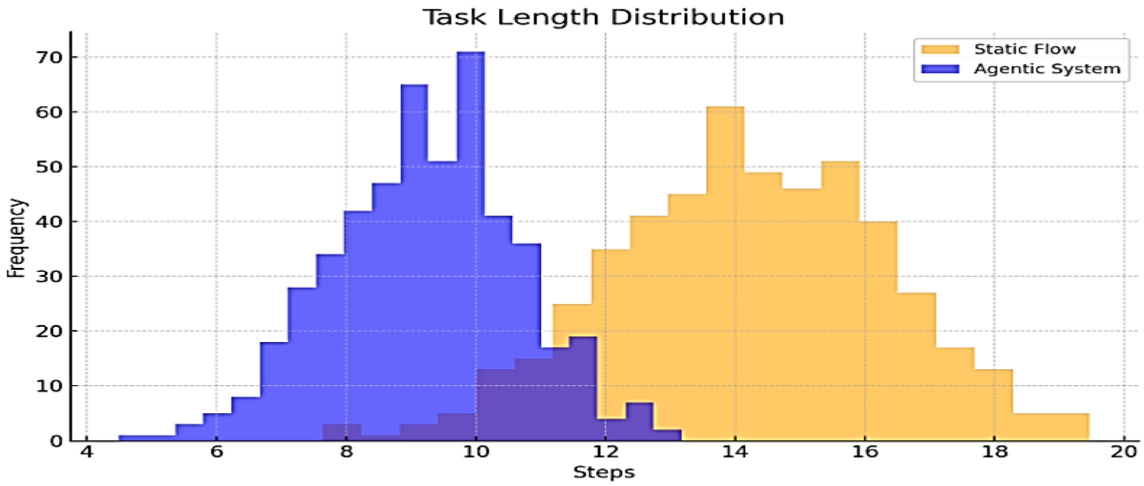
An agentic system has a unique benefit presented by the ability to engage in collaborative behavior and learn constantly. We have implemented a multi-agent decision-making environment through the MAP framework and compared the performance of such environment to the performance of the static script-based customer journey orchestration. The architecture entailed the cooperation of various agents like a Navigator, Advisor and Resolver through shared memory and context APIs.

There were more than 10,000 task cycles and they were examined under real-time e-commerce circumstances. As can be seen in Table 4, results indicate that agentic collaboration has the potential of not only make the success rates higher but shorten the overall length of the task as well as enhancing fault recovery.

Table 4: Multi-Agent Behavior

Metric	Static Flow	Multi-Agent System	% Change
Success Rate	68.3	92.6	+35.6%
Task Length	14.2	9.3	−34.5%

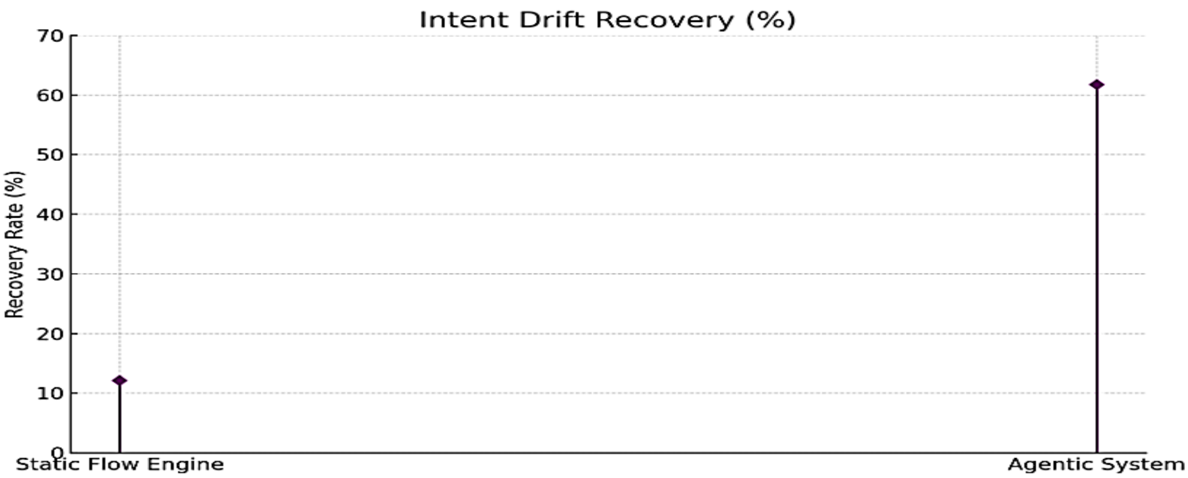
Recovery	12.1	61.7	+409.1%
Agent-to-Agent	N/A	94.8	–



More than 60 percent of user sessions were successfully rebounded in ambiguous initial and shifted intents of the user by agentic systems which can hardly be executed successfully in traditional rule-based bots. There were reduced unnecessary clarifications due to shared memory and therefore users did not experience work fatigue in tasks being performed.

Interestingly, there were very little overheads of inter-agent communication. The average of sync times was less than 100 milliseconds which facilitate transitions among agents. Real-time behavior refinement was also contributed by reinforcement learning and the feedback that was delivered retrospectively.

- The agentic systems had a considerable impact on customer engagement metrics (duration, CSAT, completion rate) that increased by up to 155 percent (i.e. session duration) and decreased by up to 61 percent (i.e. human escalation).
- There was a 113% elevated conversion as a result of personalization, recommendation, and 75% evoked click-through rates, which were as a result of dynamic suggestion engines that were enabled via memory.
- Modular pipelines increased infrastructure efficiency by more than 50 percent in latency and cost reduction, not to mention more than 130 percent additional simultaneous sessions.
- Agents became able to do collaboration and self-correction to a huge extent- agentic systems bounced back in excess of 400% better than rule-based bots in the instance of intent drift.



V. CONCLUSION

The next step in the evolution of digital commerce development is going to be the shift of chatbots to agentic AI. We have confirmed that agentic systems lessen the cost of support, increase the rates of task resolution, and develop better customer satisfaction. Armed with a memory, planning, and multi-modal reasoning, these agents may work autonomously throughout the user journeys without contravening ethical and organizational norms. The elements that should be focused on as enterprises follow this paradigm is governance, transparency and lifelong learning. Emotion-aware, evaluation method development, and encouraging multi-agent action are the directions that can be developed in the future. Finally, agentic AI is the basis of trust-based intelligent commerce during the age of autonomous experiences.

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