Measuring the effectiveness of AI-enabled chatbots in customer service using AnyLogic simulation

Xu Sun[1] , Hao Yu[1], Wei Deng Solvang[1]

Abstract. With the rapid technological advancement and innovation in Industry 4.0/5.0, digitalization has become the mainstream that transforms the paradigm of many industries, businesses, and services. In this regard, AI-enabled chatbots have been increasingly adopted by many companies for providing customer services instead of human agents. On the one hand, the use of AI-enabled chatbots provides opportunities to reduce customers' waiting time, improve efficiency, and minimize costs. On the other hand, it may, however, negatively affect customers' experiences due to several reasons, e.g., unfamiliarity with the IT system, incapability to properly answer individualized questions by chatbots, etc. Several qualitative analyses have been done to investigate the benefits and challenges of using AI-enabled chatbots for companies and also to reveal the customers' perceptions and experiences, but there is still a lack of quantitative research that may help companies to adopt this new technology in their customer service. To fill this gap, in this paper, we develop a discrete event simulation model using the AnyLogic simulation software package to measure the effectiveness of AI-enabled chatbots, which, through scenario analyses, provides managerial implications related to the average time in the system, response rate, satisfaction level, and cost savings. Thus, this method can help companies with a better understanding of the impact of adopting AI-enabled chatbots in their customer service.

Keywords: chatbot, customer service, service industry, discrete event simulation, AnyLogic

1 Introduction

Industrial revolutions are driven by both changing customer demands and technological advancement. Recently, the rapid development of several disruptive technologies, e.g., the Internet of things (IoT), artificial intelligence (AI), smart robots, digital twin, etc., has provided new opportunities to fulfill diversified and individualized customer demands [1, 2]. By increasingly adopting these technological enablers, the fourth industrial revolution, namely Industry 4.0, emphasizes the connectivity and intelligence of a smart manufacturing or logistics system [3]. While Industry 5.0, on the other hand, primarily focuses on the sustainability issues and the role of humans in industrial and

[1] Xu Sun, Hao Yu (✉) and Wei Deng Solvang
Department of Industrial Engineering, UiT The Arctic University of Norway, 8514 Narvik, Norway
{xu.sun, hao.yu, wei.d.solvang}@uit.no

societal transition [4]. In the Industry 4.0/5.0 era, digitalization has become the mainstream that transforms the paradigm of many industries, businesses, and services. In this regard, among other applications, AI-enabled chatbots have recently received tremendous popularity and been widely implemented in different fields, e.g., education [5], medical and healthcare systems [6], service systems [7], digital workplace [8], entertainment industry [9], etc. During the COVID-19 pandemic, the development of IT-platform with AI-enabled chatbots has been unprecedentedly focused on by a large number of worldwide companies [10].

AI-enabled chatbots are considered a class of software applications, which have the capability of communicating with people in natural languages [11]. They are viewed as one of the most important gamechanger for providing online customer service [12], which may help to drastically reduce the labor cost and improve the service level [10]. A recent survey illustrates that approximately 31% of companies and organizations interviewed have already implemented or have a plan to implement AI-enabled chatbots in their online customer service systems [13]. In the United States, more than 40% of retail customers have the experience of using AI-enabled chatbots [14]. Moreover, it is becoming common practice to implement AI-enabled chatbots in the customer service of many industries, i.e., banking and financial service [15], hotel service [16], and insurance [17].

There are several types of AI-enabled chatbots that may provide different functionalities and services. For example, some chatbots can provide customers with the required information and help from a company or a service provider [10]. On the other hand, some other chatbots are more intelligent and interactive to continuously provide personalized assistance to the users, such as Siri and Google Assistant. In this paper, we consider two different ways of categorization of AI-enabled chatbots in customer service. First, they can be categorized into three types based on the response mechanism:

- *Rule-based mechanism*: the conversation is based on several predefined rules.
- *AI-based generative mechanism*: the chatbots can generate new and more proper answers to interact with users [18].
- *Hybrid mechanism*: it combines both mechanisms above.

Based on the domain of knowledge for the human-chatbot interaction, they can be categorized into two types:

- *Closed-domain*: the chatbot is only capable of answering the questions from the predefined domain of knowledge [9].
- *Open-domain*: the chatbot is not restricted by the domain of knowledge and can answer questions in all fields.

For assisting in customer service, the majority of AI-enabled chatbots operate with a hybrid response mechanism with a closed domain of knowledge. The successful implementation of AI-enabled chatbots in customer service depends heavily on the customer experience [10]. On the one hand, the increasing use of AI-enabled chatbots may help companies drastically reduce the cost of personnel and training [19, 20], while, at the same time, it may positively influence the customer experiences [21] by, for example, reducing customers' waiting time and improve efficiency [22]. On the other hand, it may, however, negatively affect customers' experiences due to several reasons. For instance, the users, especially the aging population, may be unfamiliar with the IT systems. The chatbot may be incapable of understanding the questions and providing the proper answers to solve the problem [14]. Besides, research also suggests there is also a data security concern related to the conversation with the chatbots [23], particularly in banking and financial service [24].

Several studies have been conducted to investigate the benefits of using AI-enabled chatbots [25] and to understand the customers' experiences in both positive and negative aspects [26, 27]. However, these studies are of qualitative nature, and research has been done with a qualitative method. Therefore, to fill this gap, we develop a discrete event simulation model using the AnyLogic simulation package to measure the effectiveness of AI-enabled chatbots, which can provide a thorough scenario analysis and help companies in the decision-making of the adoption of AI-enabled chatbots for their customer service.

The rest of this paper is organized as follows: Section 2 provides the problem description and the simulation method. Section 3 shows the test scenarios, experiments, results, and discussions. Finally, the conclusion and future research directions are given in Section 4.

2 Problem description and methodology

In this section, the problem description is first given, and then the simulation model is developed.

2.1 Problem description

To measure the effectiveness of implementing AI-enabled chatbots in customer service, we present a comparative study with the traditional customer service system with only human agents. Taking into account the effectiveness of chatbots in properly answering the questions from customers and the number of human agents, several scenarios are defined to compare the two systems concerning the following criteria:

- Customer inquiry response rate
- Average time in the system
- Waiting time/queue length
- Customer satisfaction rate
- Cost savings

2.2 Discrete event simulation model in AnyLogic

Discrete event simulation is an analytical method that models the dynamics and measures the system performance through the changing states of a set of discrete sequential events. AnyLogic is one of the most powerful simulation software packages for creating a discrete event simulation model for a system, and it has been widely used to solve a large variety of problems in many fields, e.g., printing systems at a university [28], urban postal counter locations [29], lean adoption at a factory [30], etc. In this paper, we use AnyLogic to build two systems, namely, the traditional customer service system and the chatbot-added customer service system. Figs. 1 and 2 illustrate the flowcharts of both customer service systems.

The same distribution is used to simulate the customer arrival rate in both traditional and chatbot-added customer service systems. In the traditional system, all customers wait in a queue before receiving the service from an agent, and some customers will be dissatisfied and quit if the waiting time is too long. The average time in the system and the satisfaction level are associated with the number of agents in the system. In the chatbot-added system, the incoming customers can be immediately served by a chatbot without waiting time. Some inquiries can be solved in this stage by the chatbot, and the other inquiries are then re-directed to the human agents. After that, it is similar to the traditional system, and customers need to wait in a queue. In the chatbot-added system, customers may quit at any stage due to dissatisfaction with the IT system and the long waiting time for the human agent, so the average time in the system and the satisfaction level are determined by the intelligence level of the chatbot and the number of human agents.

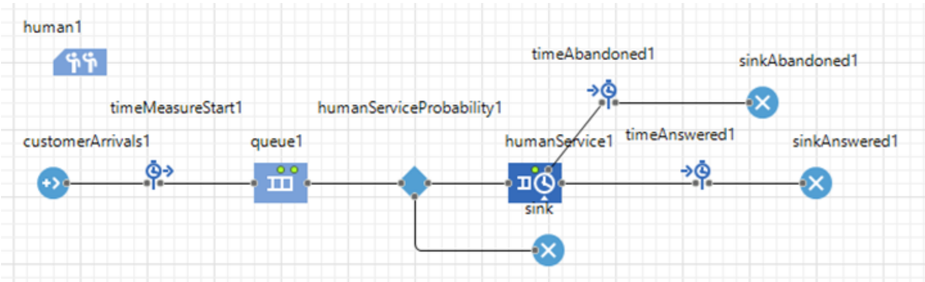

Fig. 1. Flowchart of the traditional customer service system.

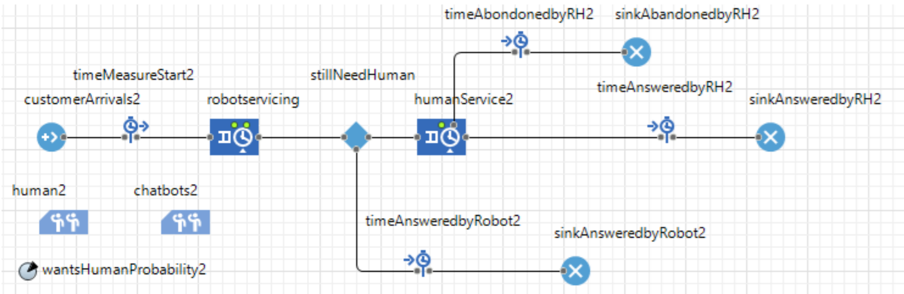

Fig. 2. Flowchart of the chatbot-added customer service system.

3 Experiments, Results, and Discussion

To compare the two customer service systems under different conditions, we set up 6 scenarios in the experiment, as shown in Table 1. In the traditional system, 5 agents were employed to provide customer service. In the chatbot-added system, the number of human agents was set to 2 and 3 in different scenarios. Considering the variation in the intelligence level, we tested three different chatbot service rates at 30%, 40%, and 50%, respectively. Table 2 presents the setting of the parameters in the simulation experiments, where stochastic parameters are used to analyze the impact of uncertainty. A satisfaction rate is given for the customer service provided by the human agents in both systems.

Table 1 Test scenarios of the experiment.

Scenarios	Traditional system	Chatbot-added system	
	Number of agents	Chatbot service rate	Number of agents
1	5	30%	2
2	5	40%	2
3	5	50%	2
4	5	30%	3
5	5	40%	3
6	5	50%	3

Table 2 The parameter setting in the experiment.

Key parameter	Traditional system	Chatbot-added system
Customer arrival rate (min.)	Triangular (0, 3, 1)	Triangular (0, 3, 1)
Queue capacity (customers)	30	30
Human service time (min.)	Triangular (2, 12, 8)	Triangular (2, 12, 8)
Chatbot service time (min.)	-	Triangular (1, 10, 5)
Timeout (min.)	Triangular (2, 15, 8)	Triangular (2, 15, 8)
Chatbot service rate	-	30%, 40%, 50%
Satisfaction value	Triangular (0.6, 1, 0.85)	Triangular (0.6, 1, 0.85)
Total number of customers	5000	5000

Fig.3 illustrates the comparison of the response rates of both traditional and chatbot-added customer service systems. With 5 agents, the response rate of the traditional system is 62%, and 38% of customers quit the queue due to the long waiting time. However, the response rate of the chatbot-added systems is drastically affected by both the intelligence level and the number of human agents. In the first three scenarios with 2 human agents, the response rates are 46%, 56%, and 65% with the increase of the intelligence level of the chatbot. By introducing another human agent, the response rate can be improved to 54%, 63%, and 74% in scenarios 4, 5, and 6.

In the traditional system, the customer satisfaction value, average time in the system, queue length, and agent utilization are 0.507, 13.5 minutes, 6.8 customers, and 100%, respectively. Table 3 presents the relevant indicators for the chatbot-added customer service system. First, with the given customer arrival pattern, the agent utilization in both customer service systems reaches nearly 100%. When 2 human agents are used in the chatbot-added system, a better service level can only be achieved in scenario 3 with the satisfaction value of 0.531. Compared with the traditional system, the average time in the system and the queue length can be reduced to 12.9 minutes and 6.6 customers. When 3 human agents are employed in scenarios 4, 5, and 6, the satisfaction value can be improved by 0.007 with a 40% chatbot service rate. However, in this scenario, the average time in the system and the queue are longer than that in the traditional customer service system. Finally, when the chatbot service rate increases to 50% in scenario 6, the satisfaction value can be increased by 0.99, and the average time in the system and the queue length can be reduced to 12.5 minutes and 5.9 customers, respectively.

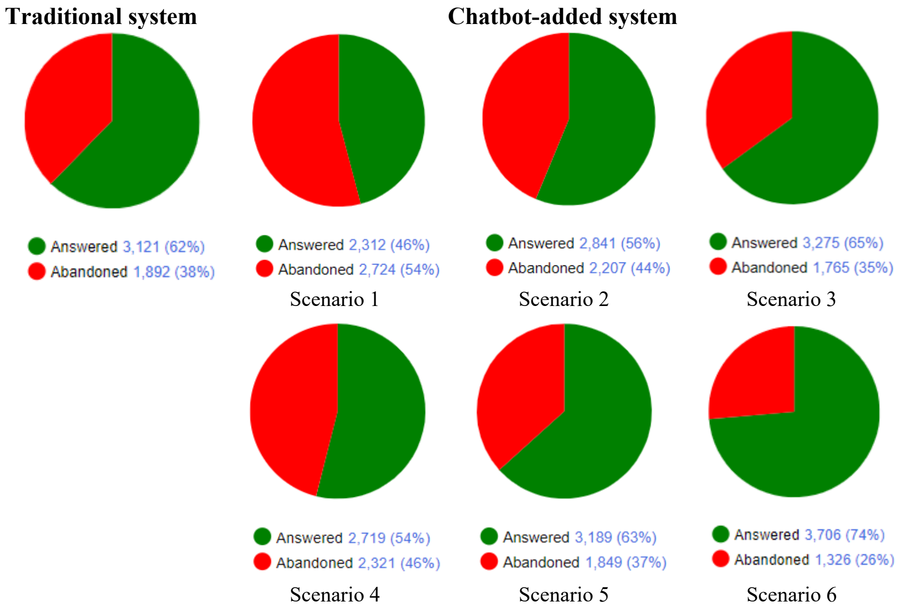

Fig. 3. Comparison of the response rate of both systems in the test scenarios.

Table 3 Experimental results of the chatbot-added system.

Scenarios	Satisfaction	Average time (min.)	Queue length (customers)	Agent utilization
1	0.376	16.6	9.4	100%
2	0.458	14.8	7.9	100%
3	0.531	12.9	6.6	99%
4	0.442	16.2	8.9	100%
5	0.514	14.4	7.6	99%
6	0.606	12.5	5.9	99%

Finally, the implications related to cost-saving are discussed. To reach the same service level as the traditional system, both the intelligence level and the number of human agents play important roles. For example, if the chatbot is intelligent enough to reach a 50% service rate, the labor cost of the customer service system can be reduced by 60%. On the other hand, when the chatbot service rate becomes 40%, a 40% reduction in labor costs can be achieved to maintain a similar service level.

4 Conclusion

The use of AI-enabled chatbots in customer service has been increasingly focused on due to their potential for improving service efficiency, customer satisfaction, and cost-saving. In this paper, a discrete event simulation model is developed using the AnyLogic simulation software package, which aims at providing quantitative insights into the key performance indicators and also at guiding companies to better adopt this new technology in their customer service. The experiment compares the traditional customer service system with the chatbot-added customer service system in several criteria, e.g., customer response rate, average time in the system, queue length, etc. The results show that the use of AI-enabled chatbots can drastically reduce labor costs and improve the customer service level. However, it is also noted that chatbots cannot completely replace human services, and their intelligence level and problem-solving capability are the most important factors to determine the cost savings.

Finally, for future improvement of this research, a more comprehensive analysis of the customer behavior in both customer service systems needs to be conducted so that the simulation can be improved to better capture the features and re-create the close-to real-life systems. Besides, the simulation model also needs to be validated with more real-world data.

References

1. Yu, H., Solvang, W.D.: Enhancing the competitiveness of manufacturers through Small-scale Intelligent Manufacturing System (SIMS): A supply chain perspective. In: 2017 6th International Conference on Industrial Technology and Management (ICITM), pp. 101-107. IEEE, (Year)
2. Zhang, C., Chen, D., Tao, F., Liu, A.: Data driven smart customization. Procedia CIRP 81, 564-569 (2019)
3. Sun, X., Yu, H., Solvang, W.D., Wang, Y., Wang, K.: The application of Industry 4.0 technologies in sustainable logistics: A systematic literature review (2012–2020) to explore future research opportunities. Environmental Science and Pollution Research 1-32 (2021)
4. Jafari, N., Azarian, M., Yu, H.: Moving from Industry 4.0 to Industry 5.0: What Are the Implications for Smart Logistics? Logistics 6, 26 (2022)
5. Winkler, R., Söllner, M.: Unleashing the potential of chatbots in education: A state-of-the-art analysis. In: Academy of Management Annual Meeting (AOM). (Year)
6. Walss, M., Anzengruber, F., Arafa, A., Djamei, V., Navarini, A.A.: Implementing medical chatbots: an application on hidradenitis suppurativa. Dermatology 237, 712-718 (2021)
7. Weißensteiner, A.A.A.: Chatbots as an approach for a faster enquiry handling process in the service industry. Signature 12, (2018)
8. Meyer von Wolff, R., Hobert, S., Masuch, K., Schumann, M.: Chatbots at digital workplaces–a grounded-theory approach for surveying application areas and objectives. Pacific Asia Journal of the Association for Information Systems 12, 3 (2020)
9. Adamopoulou, E., Moussiades, L.: Chatbots: History, technology, and applications. Machine Learning with Applications 2, 100006 (2020)
10. Nicolescu, L., Tudorache, M.T.: Human-Computer Interaction in Customer Service: The Experience with AI Chatbots—A Systematic Literature Review. Electronics 11, 1579 (2022)
11. Dale, R.: The return of the chatbots. Natural Language Engineering 22, 811-817 (2016)
12. Nordheim, C.B., Følstad, A., Bjørkli, C.A.: An initial model of trust in chatbots for customer service—findings from a questionnaire study. Interacting with Computers 31, 317-335 (2019)

13.Manusama, B., Bharaj, G.: Market Guide for Virtual Customer Assistants. (2016)
14.Følstad, A., Taylor, C.: Investigating the user experience of customer service chatbot interaction: a framework for qualitative analysis of chatbot dialogues. Quality and User Experience 6, 1-17 (2021)
15.Jang, M., Jung, Y., Kim, S.: Investigating managers' understanding of chatbots in the Korean financial industry. Computers in Human Behavior 120, 106747 (2021)
16.Buhalis, D., Cheng, E.S.Y.: Exploring the use of chatbots in hotels: technology providers' perspective. Information and communication technologies in tourism 2020, pp. 231-242. Springer (2020)
17.Nuruzzaman, M., Hussain, O.K.: IntelliBot: a dialogue-based chatbot for the insurance industry. Knowledge-Based Systems 196, 105810 (2020)
18.Gao, C., Lei, W., He, X., de Rijke, M., Chua, T.-S.: Advances and challenges in conversational recommender systems: A survey. AI Open 2, 100-126 (2021)
19.Hildebrand, C., Bergner, A.: AI-Driven Sales Automation: Using Chatbots to Boost Sales. NIM Marketing Intelligence Review 11, (2019)
20.Anagnoste, S., Biclesanu, I., D'Ascenzo, F., Savastano, M.: The role of chatbots in end-to-end intelligent automation and future employment dynamics. Business revolution in a digital era, pp. 287-302. Springer (2021)
21.Grewal, D., Herhausen, D., Ludwig, S., Ordenes, F.V.: The future of digital communication research: Considering dynamics and multimodality. Journal of Retailing 98, 224-240 (2022)
22.Karhunen, J.: Implementing Chatbots in the Customer Service Process to Reduce Workload. (2020)
23.Völkle, C., Planing, P.: Digital automation of customer contact processes–an empirical research on customer acceptance of different Chatbot use-cases. Digitalen Wandel gestalten, pp. 217-229. Springer (2019)
24.Lai, S.-T., Leu, F.-Y., Lin, J.-W.: A banking chatbot security control procedure for protecting user data security and privacy. In: International conference on broadband and wireless computing, communication and applications, pp. 561-571. Springer, (Year)
25.Reinartz, W., Wiegand, N., Imschloss, M.: The impact of digital transformation on the retailing value chain. International Journal of Research in Marketing 36, 350-366 (2019)
26.Følstad, A., Skjuve, M.: Chatbots for customer service: user experience and motivation. In: Proceedings of the 1st international conference on conversational user interfaces, pp. 1-9. (Year)
27.Cheng, Y., Jiang, H.: How do AI-driven chatbots impact user experience? Examining gratifications, perceived privacy risk, satisfaction, loyalty, and continued use. Journal of Broadcasting & Electronic Media 64, 592-614 (2020)
28.Sun, X., Yu, H., Solvang, W.D.: Solving the location problem of printers in a university campus using p-median location model and AnyLogic simulation. In: International Workshop of Advanced Manufacturing and Automation, pp. 577-584. Springer, (Year)
29.Yu, H., Sun, X., Solvang, W.D., Laporte, G.: Solving a Real-World Urban Postal Service System Redesign Problem. Scientific Programming 2021, (2021)
30.Ahmed, A., Page, J., Olsen, J.: Adopting lean six sigma to AnyLogic simulation in a manufacturing environment. In: 21st International congress on Modelling and simulation, Gold Coast, Australia,(29 November to 04 December, 2015), pp. 29-35. (Year)