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Directions of the 100 most cited chatbot-related human behavior research: A review of academic publications

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ABSTRACT

Chatbots are becoming a common trend in the service industry, education, and daily life. Increasing evidence has shown that chatbots have the potential to change the way people learn and search for information in human behavior. However, a systematic review of chatbot-related human behavior research with high citation rates has not been performed. Papers with high citation rates represent the latest changes in a particular research field, and reflect the current issues or research trends. By reading highly cited papers, researchers can identify important research questions. Therefore, this article presents a systematic literature review exploring the latest changes in chatbot research, and reviews the top 100 highly cited articles. The review shows that the highly cited chatbot-related studies have proposed new conversation strategies and compared different modes of human–human online conversations and human–chatbot conversations to find more effective methods of online communication. In addition, existing research has focused on high-level statistical performance and system development and testing. The findings also show that chatbots have started to be applied to the field of education, and there is much potential for the use of chatbots to improve the learning process and learning outcomes.

1. Introduction

With advances in computer technologies, in particular, artificial intelligence, computer systems are able to provide educational supports in a friendlier and smarter manner (Chen, Xie, Zou, et al., 2020; Hwang, Xie, et al., 2020). Among various computer systems, chatbots have been recognized as an effective way to promote interpersonal communication and educational applications in human behavior (Chen, Xie, Zou, et al., 2020; Lin, Tu, et al., 2021; Tang et al., 2021). A chatbot is artificially constructed software that uses natural language as input and output to talk to humans. Chatbots can act as a personal assistant on mobile devices to provide users with personalized information, enable real-time social interaction media, and can even be used in health consultations (Poncette et al., 2020; Muniasamy and Alasiry, 2020; Yamada et al., 2016). Chatbots are increasingly being used in instant messaging and are being implemented in people's regular lives, shopping experiences, and education courses (Ferrell and Ferrell, 2020). Several studies have revealed that chatbots can bring entertainment to users, provide instant feedback, enhance peer communication skills (Hill et al., 2015), and improve students' learning efficiency (Wu et al., 2020).

As mobile technology changes the way of communication, chatbots are becoming increasingly popular in interactions with users and are becoming rapidly popularized and adopted, allowing them to be developed and applied to various environments. Smutny and Schreiberova (2020) analyzed Facebook Messenger as an educational chatbot platform to support learning. The authors categorized 89 unique chatbots by language, topic, and developer platform. Educational chatbots used on the Facebook Messenger platform are different from sending personalized messages. The results showed that chatbots for instant messaging are still in the early stages, but they could incorporate artificial intelligence (AI) to become teaching assistants in the future (Hwang, Sung, et al., 2020; Lin, Chai, et al., 2021; Yang et al., 2021). The research results highlighted the feasibility of integrating chatbots into classroom practice (Smutny and Schreiberova, 2020). In line with the Internet of Things (IoT) and AI era, machine learning, and natural language applications, chatbots have become a hot research topic in academia (Chen, Xie, Hwang, 2020; Hwang, Xie, et al., 2020). Although some recent research studies have reviewed the use of chatbots (Abd-alrazaq et al., 2019, 2020; Bendig et al., 2019; Serban et al., 2018), they have tended to focus on using chatbots to foster mental health

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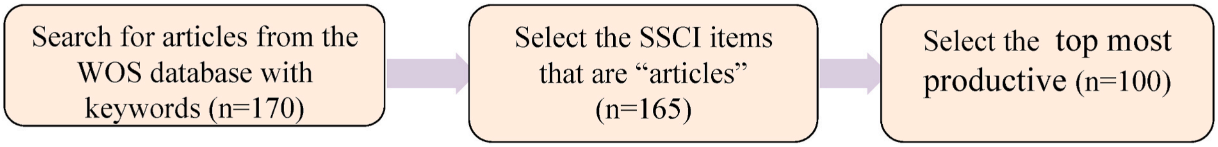

Fig. 1. Data collection procedure.

recommendations, health care issues, and data-driven dialogue systems.

A chatbot, also referred to as a virtual agent or chatterbot, is a machine conversation system that performs natural language dialogue (Brennan, 2006; Hsieh, 2011; Melián-González et al., 2019). According to the previous reference, ELIZA was the first chat robot to use keyword or pattern matching mechanisms to find interactive patterns and give users a relative response, known as the ELIZA mechanism (Weizenbaum, 1966). Amazon Echo supports many purposes and forms of human-to-human talk, and the human–computer dialogue system also allows for many forms of interaction, such as the chat function for emotional companionship (Wilks, 2010). Initially, chatbots were developed for entertainment purposes with simple keyword matching technology. Innovations such as Siri added a voice user interface (VUI) to the traditional mobile graphical user interface (GUI) (Guttormsen et al., 2011). The revolutionary innovation of the human–machine dialogue system was launched in 2014 when Amazon Echo was released. Amazon Echo is hardware based entirely on voice interaction, and its voice technology support is far more advanced than that of Siri (Natale, 2020). Task-based dialogues, which enable users to collect information to complete a form-filled task, such as booking an air ticket, have a wide range of e-commerce roles and ubiquitous sales potential (Moriuchi et al., 2020). Active dialogue allows the machine to initiate a topic, which is different from the previous interactions that are initiated by people (Chopra et al., 2016).

Human–machine dialogue and conversation interaction systems have become the main interactive methods in the IoT era (Abdul-Kader and Woods, 2015). For example, Følstad and Brandtzæg (2017) claimed that some companies, such as Google, Facebook, and Microsoft, consider chatbots to be the next popular technology. For instance, Fryer et al. (2019) explained that chatbots were originally based on computer language experiments, which conformed to the basic nature of language applications. Research has been applied to text chat between robots and humans, where robots take charge of the initial dialogue and classify the content of the user's dialogue. Winkler and Soellner (2018) presented the four main advantages of chatbots: they (1) perform personal assistant functions, (2) save customer service costs, (3) improve user satisfaction, and (4) predict customer problems and proactively interact with users 24 h a day to provide the information that they need. Therefore, the system analysis of chatbots can be performed through user dialogue to gain a better understanding of customer needs and to improve academic research work and service quality.

2. Research purpose

Many previous studies have examined the use of chatbots through scoping reviews. For example, Abd-alrazaq et al. (2019) analyzed the application of chatbots in the field of mental health, Abd-alrazaq et al. (2019) evaluated healthcare chatbots, and Bendig et al. (2019) analyzed the application of chatbots in clinical psychology and psychotherapy to improve mental health. The findings of these scoping reviews have indicated that chatbots have become an important trend in research. However, despite the sharp increase in the amount of research related to chatbots, current research is limited to reviews in the medical field, and few reviews have analyzed the predominant focus of highly cited chatbot research. Therefore, this article identifies the highly cited papers and determines the areas of application for chatbots. This article also identifies the important issues on which scholars have focused, and so can serve as a reference for the future research and discussions of chatbots.

In addition, there is no research that examines the characteristics of the most highly cited articles on chatbots. To address this gap, this study examines the research trends of the 100 most cited articles about chatbots published in Social Science Citation Index (SSCI) journals. This research proposes the following research questions:

1. Which countries are the top most productive among the 100 highly cited articles?
2. In terms of interaction, what are the top most productive journals from the top 100 highly cited articles related to chatbots?
3. What are the research fields and application domains of the top 100 highly cited articles?
4. What are the adopted technologies in the top 100 highly cited articles?
5. What are the research designs and analysis methods used in the top 100 highly cited articles?
6. Who are the top 10 most productive authors of the top 100 highly cited articles?

3. Research methods

3.1. Resources

Sentiment analysis has become an active subject of study since 2000. To ensure full coverage of the targeted articles, the search aimed to retrieve relevant articles published between 1999 and 2020. Using the Web of Science (WoS) database, the search of SSCI publications was conducted on August 8, 2020 using the keyword “chatbot”; 170 papers were initially retrieved. According to recommendations by Chang et al. (2018), the document type was limited to “articles”; thus, five articles were discarded, leaving 165 papers for review. These 165 articles were sorted by the number of citations from high to low, and the top 100 papers were selected for analysis. The articles were analyzed using the VOSviewer software, which was developed using the Java programming language. Because Java is platform-independent, VOSviewer runs on most hardware and operating system platforms. VOSviewer can be used freely for any purpose. Fig. 1 shows the procedure to search for the top 100 highly cited chatbot-related human behavior research.

Table 1 shows the results of the search. From the table, it was found that a portion of the articles had only been cited once. This implies that “chatbots in human behavior” is still a new research direction. Meanwhile, the number one article has been cited 73 times, showing the potential of this research domain.

3.2. Data distribution

Fig. 2 shows the publication status of the highly cited chatbot papers and the top 100 highly cited papers published between 2000 and 2020. The discovery of the pioneer chatbot dates back to 2003, with Tatai, Csordás, and Kiss's (2003) design of a platform system that supports chatbots. Notably, more than half of the highly cited papers were published between 2018 and 2020, indicating the increased attention to the research on chatbots in recent years. Some valuable research studies have highlighted some innovative problems (Abd-alrazaq et al., 2019, 2020; Bendig et al., 2019). For example, Kerlyl et al. (2007) brought chatbots into the field of education and discussed the development and

Table 1
The top 100 highly cited Chatbot papers.

Rank	Year	Authors	Citation rate	Paper title
1	2015	Hill, J; Ford, WR; Farreras, IG	73	Real conversations with artificial intelligence: a comparison between human-human online conversations and human-chatbot conversations
2	2009	Lee, C; Jung, S; Kim, S; Lee, GG	58	Example-based dialogue modeling for practical multi-domain dialogue system
3	2007	Kerly, A; Hall, P; Bull, S	54	Bringing chatbots into education: towards natural language negotiation of open learner models
4	2008	Kerly, A; Ellis, R; Bull, S	42	CAL system: a conversational agent for learner modelling
5	2018	Araujo, T	38	Living up to the chatbot hype: the influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions
6	2011	Crutzen, R; Peters, GJY; Portugal, SD; Fisser, EM; Grolleman, JJ	38	An artificially intelligent chat agent that answers adolescents' questions related to sex, drugs, and alcohol: an exploratory study
7	2016	Sundar, SS; Bellur, S; Oh, J; Jia, HY; Kim, HS	37	Theoretical importance of contingency in human-computer interaction: effects of message interactivity on user engagement
8	2009	Jia, JY	29	CSIEC: a computer assisted English learning chatbot based on textual knowledge and reasoning
9	2017	Ly, KH; Ly, AM; Andersson, G	23	A fully automated conversational agent for promoting mental well-being: a pilot rct using mixed methods
10	2017	D'Alfonso, S; Santesteban-Echarri, O; Rice, S; Wadley, G; Lederman, R; Miles, C; Gleeson, J; Alvarez-Jimenez, M	23	Artificial intelligence-assisted online social therapy for youth mental health
11	2019	Ciechanowski, L; Przegalinska, A; Magnuski, M; Gloor, P	22	In the shades of the uncanny valley: an experimental study of human-chatbot interaction
12	2017	Fryer, LK; Ainley, M; Thompson, A; Gibson, A; Sherlock, Z	22	Stimulating and sustaining interest in a language course: an experimental comparison of chatbot and human task partners
13	2018	Fulmer, R; Joerin, A; Gentile, B; Lakerink, L; Rauws, M	21	Using psychological artificial intelligence (Tess) to relieve symptoms of depression and anxiety: randomized controlled trial
14	2018	Ho, A; Hancock, J; Miner, AS	21	Psychological, relational, and emotional effects of self-disclosure after conversations with a chatbot
15	2019	Go, E; Sundar, SS	16	Humanizing chatbots: the effects of visual, identity and conversational cues on humanness perceptions
16	2017	Mou, Y; Xu, K	16	The media inequality: comparing the initial human-human and human-AI social interactions
17	2018	Liu, BJ; Sundar, SS	12	Should machines express sympathy and empathy? experiments with a health advice chatbot
18	2006	Lu, CH; Chiou, GF; Day, MY; Ong, CS; Hsu, WL	12	Using instant messaging to provide an intelligent learning environment
19	2009	Burden, DJH	11	Deploying embodied AI into virtual worlds
20	2019	Feine, J; Gnewuch, U; Morana, S; Maedche, A	10	A taxonomy of social cues for conversational agents
21	2019	Palanica, A; Flaschner, P; Thommandram, A; Li, M; Fossat, Y	10	Physicians' perceptions of chatbots in health care: cross-sectional web-based survey
22	2018	Zarouali, B; Van den Broeck, E; Walrave, M; Poels, K	10	Predicting consumer responses to a chatbot on facebook
23	2019	Fryer, LK; Nakao, K; Thompson, A	9	Chatbot learning partners: connecting learning experiences, interest and competence
24	2017	Wang, YF; Petrina, S; Feng, F	9	VILLAGEVirtual immersive language learning and gaming environment: immersion and presence
25	2014	Coniam, D	9	The linguistic accuracy of chatbots: usability from an ESL perspective
26	2003	Tatai, G; Csordas, A; Kiss, A; Szalo, A; Laufer, L	9	Happy chatbot, happy user
27	2019	Stephens, TN; Joerin, A; Rauws, M; Werk, LN	8	Feasibility of pediatric obesity and prediabetes treatment support through tess, the AI behavioral coaching chatbot
28	2019	Chung, K; Park, RC	8	Chatbot-based heathcare service with a knowledge base for cloud computing
29	2011	Hsieh, SW	8	Effects of cognitive styles on an MSN virtual learning companion system as an adjunct to classroom instructions
30	2019	Ford, H; Hutchinson, J	7	Newsbots that mediate journalist and audience relationships
31	2012	Allison, D	7	Chatbots in the library: is it time?
32	2020	Biduski, D; Bellei, EA; Rodriguez, JPM; Zaina, LAM; De Marchi, ACB	6	Assessing long-term user experience on a mobile health application through an in-app embedded conversation-based questionnaire
33	2019	Fryer, LK	6	Getting interested: developing a sustainable source of motivation to learn a new language at school

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Table 1 (*continued*)

Rank	Year	Authors	Citation rate	Paper title
34	2019	Luo, XM; Tong, SL; Fang, Z; Qu, Z	6	Frontiers: machines vs. humans: the impact of artificial intelligence chatbot disclosure on customer purchases
35	2019	Pereira, J; Diaz, O	6	Using health chatbots for behavior change: a mapping study
36	2018	Wu, Y; Li, ZJ; Wu, W; Zhou, M	6	Response selection with topic clues for retrieval-based chatbots
37	2018	Liu, BQ; Xu, Z; Sun, CJ; Wang, BX; Wang, XL; Wong, DF; Zhang, M	6	Content-oriented user modeling for personalized response ranking in chatbots
38	2013	Lorenzo, CM; Lezcano, L; Sanchez-Alonso, S	6	Language learning in educational virtual worlds - a TAM based assessment
39	2006	Kerly, A; Bull, S	6	The potential for chatbots in negotiated learner modelling: a wizard-of-oz study
40	2020	Canhoto, AI; Clear, F	5	Artificial intelligence and machine learning as business tools: a framework for diagnosing value destruction potential
41	2019	Schmidlen, T; Schwartz, M; DiLoreto, K; Kirchner, HL; Sturm, AC	5	Patient assessment of chatbots for the scalable delivery of genetic counseling
42	2019	Song, D; Rice, M; Oh, EY	5	Participation in online courses and interaction with a virtual agent
43	2018	Riikkinen, M; Saarijarvi, H; Sarlin, P; Lahteenmaki, I	5	Using artificial intelligence to create value in insurance
44	2018	Tseng, JJ	5	Exploring TPACK-SLA interface: insights from the computer-enhanced classroom
45	2016	Reshmi, S; Balakrishnan, K	5	Implementation of an inquisitive chatbot for database supported knowledge bases
46	2016	Ward, T; Falconer, L; Frutos-Perez, M; Williams, B; Johns, J; Harold, S	5	Using virtual online simulations in Second Life (R) to engage undergraduate psychology students with employability issuess
47	2019	Moore, JR; Caudill, R	4	The bot will see you now a history and review of interactive computerized mental health programs
48	2019	Beaudry, J; Consigli, A; Clark, C; Robinson, KJ	4	Getting ready for adult healthcare: designing a chatbot to coach adolescents with special health needs through the transitions of care
49	2019	Miner, AS; Shah, N; Bullock, KD; Arnow, BA; Bailenson, J; Hancock, J	4	Key considerations for incorporating conversational AI in psychotherapy
50	2019	Piau, A; Crissey, R; Brechemier, D; Balardy, L; Nourhashemi, F	4	A smartphone chatbot application to optimize monitoring of older patients with cancer
51	2018	Okuda, T; Shoda, S	4	AI-based chatbot service for financial industry
52	2013	Pauletto, S; Balentine, B; Pidcock, C; Jones, K; Bottaci, L; Aretoulaki, M; Wells, J; Mundy, DP; Balentine, J	4	Exploring expressivity and emotion with artificial voice and speech technologies
53	2013	Griol, D; Callejas, Z	4	An architecture to develop multimodal educative applications with chatbots
54	2020	Lee, I; Shin, YJ	3	Machine learning for enterprises: applications, algorithm selection, and challenges
55	2019	Bibault, JE; Chaix, B; Guillemasse, A; Cousin, S; Escande, A; Perrin, M; Pienkowski, A; Delamon, G; Nectoux, P; Brouard, B	3	A chatbot versus physicians to provide information for patients with breast cancer: blind, randomized controlled noninferiority trial
56	2019	Natale, S	3	If software is narrative: Joseph Weizenbaum, artificial intelligence and the biographies of ELIZA
57	2019	Tsai, MH; Chen, JY; Kang, SC	3	Ask Diana: a keyword-based chatbot system for water-related disaster management
58	2018	Kucherbaev, P; Bozzon, A; Houben, GJ	3	Human-aided bots
59	2018	Yu, K; Zhao, ZJ; Wu, XY; Lin, HT; Liu, X	3	Rich short text conversation using semantic-key-controlled sequence generation
60	2017	Tandy, C; Vernon, R; Lynch, D	3	Teaching noteteaching student interviewing competencies through second life
61	2008	Pirrone, R; Russo, G; Cannella, V; Peri, D	3	GAIML: a new language for verbal and graphical interaction in chatbots
62	2004	Abu Shawar, B; Atwell, E	3	Accessing an information system by chatting
63	2020	Roca, S; Sancho, J; Garcia, J; Alesanco, A	2	Microservice chatbot architecture for chronic patient support
64	2019	Chan, HY; Tsai, MH	2	Question-answering dialogue system for emergency operations
65	2019	Cuayahuitl, H; Lee, D; Ryu, S; Cho, Y; Choi, S; Indurthi, S; Yu, S; Choi, H; Hwang, I; Kim, J	2	Ensemble-based deep reinforcement learning for chatbots
66	2019	Shorey, S; Ang, E; Yap, J; Ng, ED; Lau, ST; Chui, CK	2	A virtual counseling application using artificial intelligence for communication skills training in nursing education: development study
67	2019	Powell, J	2	Trust me, i'm a chatbot: how artificial intelligence in health care fails the turing test
68	2019	Carfora, V; Bertolotti, M; Catellani, P	2	Informational and emotional daily messages to reduce red and processed meat consumption
69	2019	Kim, J; Oh, S; Kwon, OW; Kim, H	2	Multi-turn chatbot based on query-context attentions and dual wasserstein generative adversarial networks
70	2019	Van den Broeck, E; Zarouali, B; Poels, K	2	Chatbot advertising effectiveness: when does the message get through?
71	2019		2	

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Table 1 (*continued*)

Rank	Year	Authors	Citation rate	Paper title
		McDonnell, M; Baxter, D		Chatbots and gender stereotyping
72	2019	Morelli, M	2	The athenian altar and the amazonian chatbot: a pauline reading of artificial intelligence and apocalyptic ends
73	2019	He, H; Zheng, QH; Di, D; Dong, B	2	How learner support services affect student engagement in online learning environments
74	2019	Mou, Y; Xu, K; Xia, K	2	Unpacking the black box: examining the (de) gender categorization effect in human-machine communication
75	2019	Wang, YM; Rong, WG; Ouyang, YX; Xiong, Z	2	Augmenting dialogue response generation with unstructured textual knowledge
76	2018	Ni, L; Liu, JM	2	A framework for domain-specific natural language information brokerage
77	2018	Kurachi, Y; Narukawa, S; Hara, H	2	Al chatbot to realize sophistication of customer contact points
78	2018	Benotti, L; Martinez, MC; Schapachnik, F	2	A tool for introducing computer science with automatic formative assessment
79	2003	Tatai, G; Csordas, A; Szalo, A; Laufer, L	2	The chatbot feeling - towards animated emotional ECAs
80	2020	Yoneoka, D; Kawashima, T; Tanoue, Y; Nomura, S; Ejima, K; Shi, S; Eguchi, A; Taniguchi, T; Sakamoto, H; Kunishima, H; Gilmour, S; Nishiura, H; Miyata, H	1	Early SNS-based monitoring system for the COVID-19 outbreak in Japan: a population-level observational study
81	2020	Stoeckli, E; Dremel, C; Uebernickel, F; Brenner, W	1	How affordances of chatbots cross the chasm between social and traditional enterprise systems
82	2020	Tsai, MH; Chan, HY; Liu, LY	1	Conversation-based school building inspection support system
83	2020	Janssen, A; Passlick, J; Cardona, DR; Breitner, MH	1	Virtual assistance in any context a taxonomy of design elements for domain-specific chatbots
84	2020	Hauser-Ulrich, S; Kunzli, H; Meier-Peterhans, D; Kowatsch, T	1	A smartphone-based health care chatbot to promote self-management of chronic pain (SELMA): pilot randomized controlled trial
85	2020	Poncette, AS; Rojas, PD; Hofferbert, J; Sosa, AV; Balzer, F; Braune, K	1	Hackathons as stepping stones in health care innovation: case study with systematic recommendations
86	2020	Ta, V; Griffith, C; Boatfield, C; Wang, XY; Civitello, M; Bader, H; DeCero, E; Loggarakis, A	1	User experiences of social support from companion chatbots in everyday contexts: thematic analysis
87	2020	Casillo, M; Clarizia, F; D'Aniello, G; De Santo, M; Lombardi, M; Santaniello, D	1	CHAT-Bot: a cultural heritage aware teller-bot for supporting touristic experiences
88	2020	Zhou, L; Gao, JF; Li, D; Shum, HY	1	The design and implementation of XiaoIce, an empathetic social chatbot
89	2020	Villegas-Ch, W; Arias-Navarrete, A; Palacios-Pacheco, X	1	Proposal of an architecture for the integration of a chatbot with artificial intelligence in a smart campus for the improvement of learning
90	2020	Toader, DC; Boca, G; Toader, R; Macelaru, M; Toader, C; Ighian, D; Radulescu, AT	1	The effect of social presence and chatbot errors on trust
91	2019	Melian-Gonzalez, S; Gutierrez-Tano, D; Bulchand-Gidumal, J	1	Predicting the intentions to use chatbots for travel and tourism
92	2019	Arsovski, S; Osipyan, H; Oladele, MI; Cheok, AD	1	Automatic knowledge extraction of any chatbot from conversation
93	2020	Narducci, F; Basile, P; de Gemmis, M; Lops, P; Semeraro, G	1	An investigation on the user interaction modes of conversational recommender systems for the music domain
94	2019	Przegalinska, A; Ciechanowski, L; Stroz, A; Gloor, P; Mazurek, G	1	In bot we trust: a new methodology of chatbot performance measures
95	2019	Greer, S; Ramo, D; Chang, YJ; Fu, M; Moskowitz, J; Haritatos, J	1	Use of the chatbot "Vivibot" to Deliver positive psychology skills and promote well-being among young people after cancer treatment: randomized controlled feasibility trial
96	2020	Valtolina, S; Barricelli, BR; Di Gaetano, S	1	Communicability of traditional interfaces vs chatbots in healthcare and smart home domains
97	2019	Thompson, D; Baranowski, T	1	Chatbots as extenders of pediatric obesity intervention: an invited commentary on "feasibility of pediatric obesity & pre-diabetes treatment support through tess, the AI behavioral coaching chatbot"
98	2019	Park, S; Choi, J; Lee, S; Oh, C; Kim, C; La, S; Lee, J; Suh, B	1	Designing a chatbot for a brief motivational interview on stress management: qualitative case study
99	2019	de Kleijn, R; Wijnen, M; Poletiek, F	1	The effect of context-dependent information and sentence constructions on perceived humanness of an agent in a turing test
100	2019	Kamita, T; Ito, T; Matsumoto, A; Munakata, T; Inoue, T	1	A chatbot system for mental healthcare based on SAT counseling method

capabilities of conversational agents (or chatbots) and intelligent tutoring systems. Wang, Petrina, and Feng (2017) added the Virtual Immersive Language Learning chat dialogue to the game environment to support students' English learning environment. Feine, Gnewuch, Morana, and Maedche (2019) developed a learning system of conversational agents to guide learners' inquiry learning activities. These scholars'

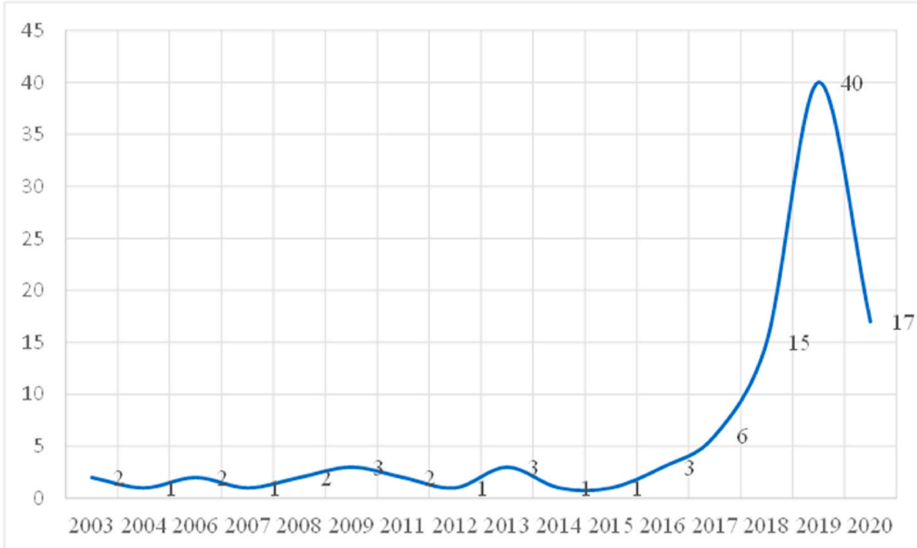

Fig. 2. Distribution status of highly cited Chatbot research.

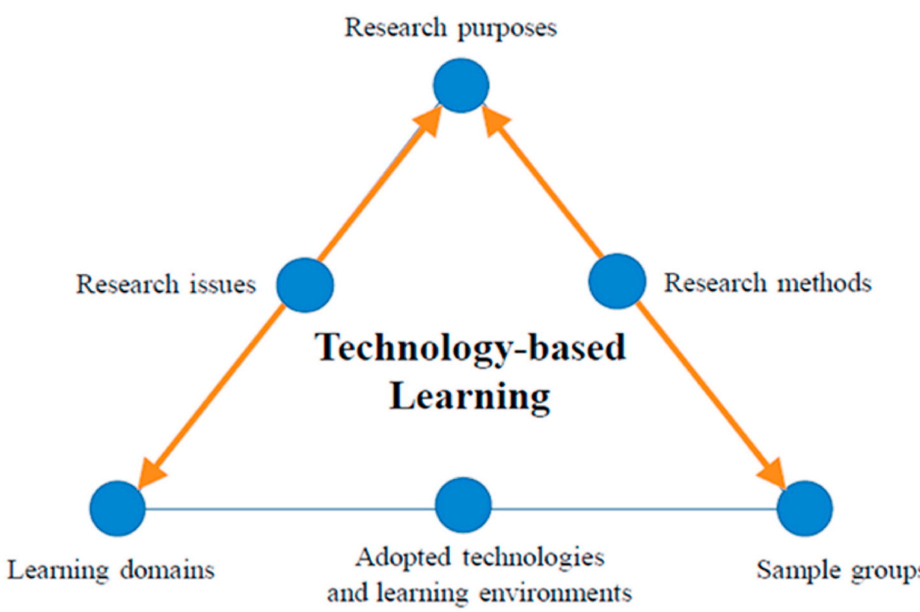

Fig. 3. Technology-based learning model for Chatbot learning.

findings suggested that research related to chatbots has shifted the development focus to the teaching environment, with the results supporting the effectiveness of chatbots in teaching.

3.3. Coding schemes

To analyze the research trend of chatbots in this study, we determined the coding scheme by referring to the Technology-based Learning Review (TLR) model (Lin and Hwang, 2019), as shown in Fig. 3. In addition, as suggested by several previous review studies (e.g., Chang et al., 2018; Hsu et al., 2012), the research fields, application domains, adopted technologies (i.e., types of chatbots), research methods, and analysis methods were taken into account in this review study, as shown in Table 2.

Lai (2020) pointed out that the productivity of each author of a research paper is valuable, and he created a series of references for related researchers. Furthermore, this study also considers the researchers' productivity based on the formula put forward by Cheng et al. (2020), which quantitatively analyzes each author's contribution to the research. To distinguish each author's contribution, a formula is used to weight the authors based on the number and order of the authors for each paper; the formula is considered to be a relatively neutral method of quantifying the author's contribution. According to the following formula, the number of citations of each paper and the total number determine the number of authors of each paper (n) and the score of the specific author's order (i). Each author is calculated as follows:

$$Score(i) = Number\ of\ citations\ \times \left(\frac{(.1.5^{n-i})}{\sum_{k=1}^{n} .1.5^{n-k}}\right)$$

For example, the scores for Chang et al. (2018) are 0.47, 0.32, and 0.21, respectively. If the number of citations of the paper is 100, in this case, the first author contributed 47 points, while the second and third authors contributed 32 points and 21 points, respectively. We used this formula to calculate the cumulative scores for all authors.

Table 2
Descriptions of these classifications are presented in the table.

Categories	Coding items	Reference
Research field	computer science information systems, computer science artificial intelligence, engineering electrical electronic, medical informatics, health care sciences services, psychology multidisciplinary, telecommunications, education educational research, business, computer science theory methods, and psychology experimental	Smutny and Schreiberova (2020)
Application domains	medical or nursing service, customer service, language learning, communication, position paper	Chang et al. (2018)
Types of chatbots	Lola, Chatbot, Dina, Smart Answering Chatbot, AutoTutor, LISA, FITEBot, Virtual Patient, FAQs Chatbot, Mobile Chatbot, NDLtutor, CALMSystem, ScratchThAI, Indigo, TOB-STT, position paper (no chatbot adopted)	Pérez et al. (2020)
Research methods	Experimental, position paper qualitative, interviews, non-experimental (survey), system design and analysis, mixed	Chang et al. (2018)
Analysis methods	Descriptive statistics, ANOVA/Mixed multivariate analysis of covariance (MANCOVA), PLS, structural equation modeling (SEM), *t*-test, Bivariate Correlations, Interviews, Chi-square tests, Confirmatory Factor Analysis, Mann-Whitney's *U* test, Others (Position paper and Analytical)	Chang et al. (2018)

4. Research results

4.1. The top most productive countries

To determine the papers' countries of origin, we only counted the nationalities of the first author of the published papers. Fig. 4 illustrates the distribution of the countries and areas with more than two published papers, the top three of which were the United States (US) (39), the United Kingdom (UK) (19), and the People's Republic of China (19).

4.2. The top most productive journals and highly cited articles

Fig. 5 shows the international journals with more than two published papers from 2003 to 2020; these included *Computers in Human Behavior*, the *Journal of Medical Internet Research*, *Knowledge-Based Systems*, *Business Horizons*, *Applied Sciences-Basel*, the *British Journal of Educational Technology*, *Cyberpsychology Behavior and Social Networking*, the *Fujitsu Scientific & Technical Journal*, *IEEE ACCESS*, *IEEE-ACM Transactions on Audio Speech and Language Processing*, *Intelligent Tutoring Systems Proceedings*, *JMIR Mhealth and Uhealth*, *Mobile Information Systems*, *Neurocomputing*, *Sustainability*, and *Translational Behavioral Medicine*. *Computers in Human Behavior* had the largest number of published papers (9), followed by the *Journal of Medical Internet Research* (7) and the *Journal of Knowledge-Based Systems* (5).

In the first 100 cited studies, the VOSviewer software analysis obtained cluster results by taking into account the articles cited more than three times, as shown Fig. 6. In this figure, the bigger circles represent more frequency cited journals. The most frequently cited journals were *Computers in Human Behavior* (N = 211 times), with a total link strength of 261, followed by *Knowledge-Based Systems* (N = 149 times), with a total link strength of 195.

4.3. Research fields and application domains

Fig. 7 presents the data distribution of research fields in the chatbots in human behavior articles. From 2003 to 2020, the field with the maximum number of publications was "computer science information systems" (30 papers), followed by "computer science artificial intelligence" (23 papers), "engineering electrical electronic" (21 papers), and "medical informatics" (21 papers). The findings revealed that chatbots have been applied to the fields of healthcare sciences services, psychology multidisciplinary, telecommunications, education educational research, business, computer science theory and methods, and experimental psychology. Thus, there is a large scope for chatbot research and related discussions.

Fig. 8 shows the application domains of the chatbots in human behavior studies. The maximum number of articles related to chatbots in human behavior research was for "position papers" (53 papers), followed by "Medical or nursing service" (26 papers), "Customer Service" (12 papers), "Language learning" (5 papers), and "Communication" (4 papers). The findings show that this research direction is new, and hence

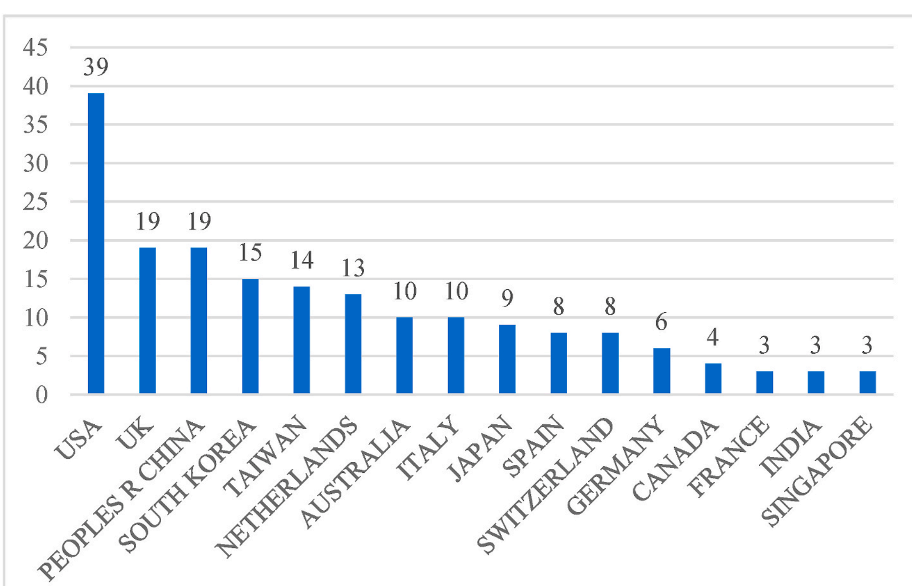

Fig. 4. Countries with more than two published papers on Chatbots.

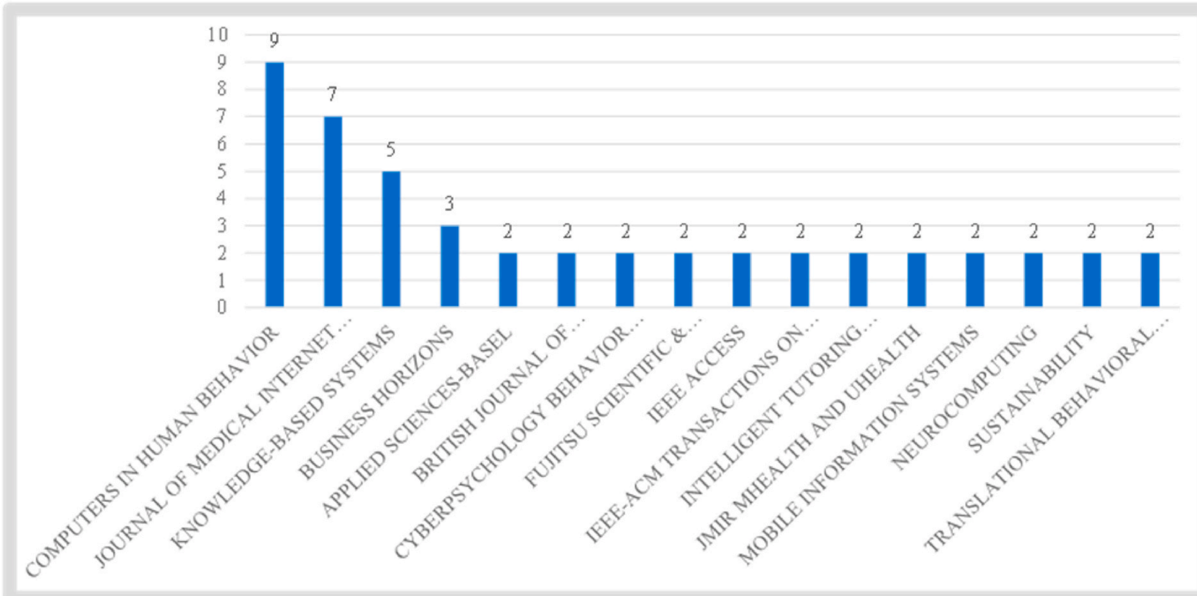

Fig. 5. Journals with more than two published papers on Chatbots.

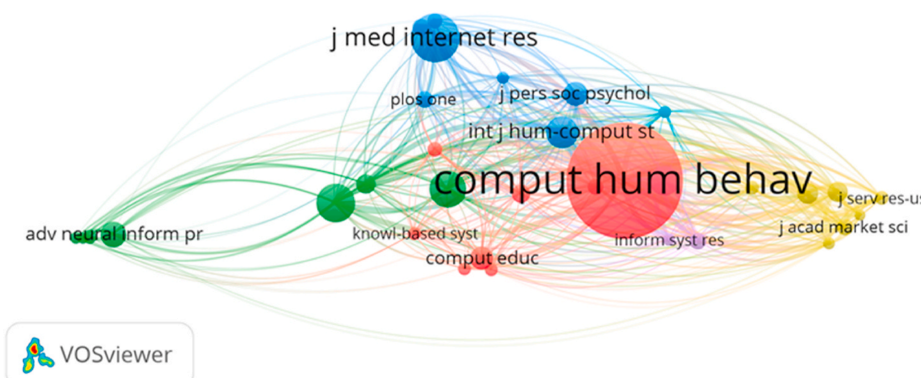

Fig. 6. The social network analysis of journals.

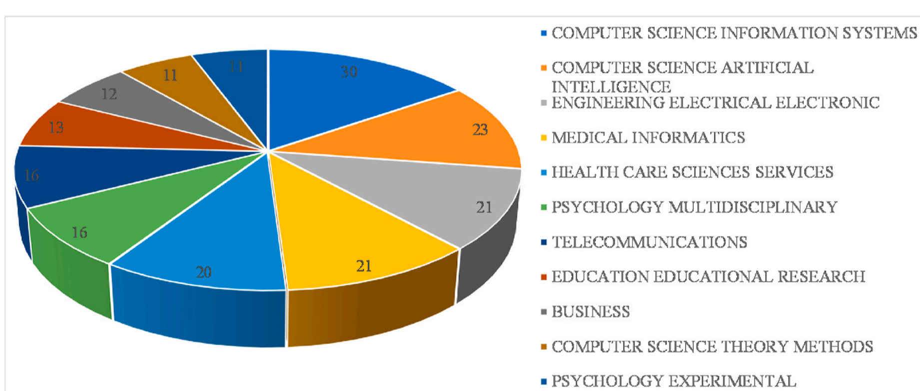

Fig. 7. Research fields of chatbot-related human behavior research.

most of the articles are position papers, in which scholars aim to articulate their positions, viewpoints, or comments regarding this particular research domain.

4.4. Types of chatbots

Fig. 9 presents the data distribution of the types of chatbots adopted in the studies. The maximum number of chatbots adopted was “CALM-System” (25 papers), followed by “Mobile Chatbot” (10 papers), “FITEBot” (6 papers), “NDLtutor” (5 papers), and “Dina” (1 paper). The

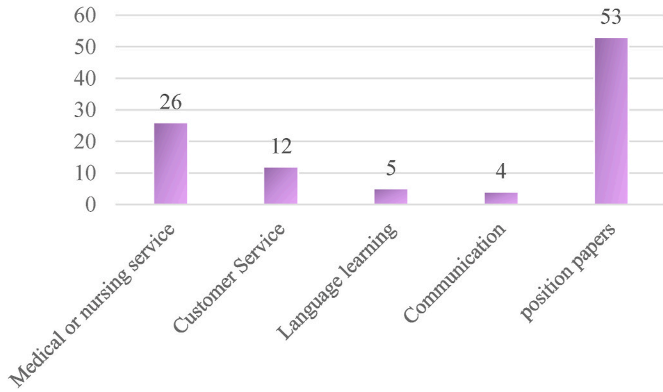

Fig. 8. Data distribution of the application domains of chatbots.

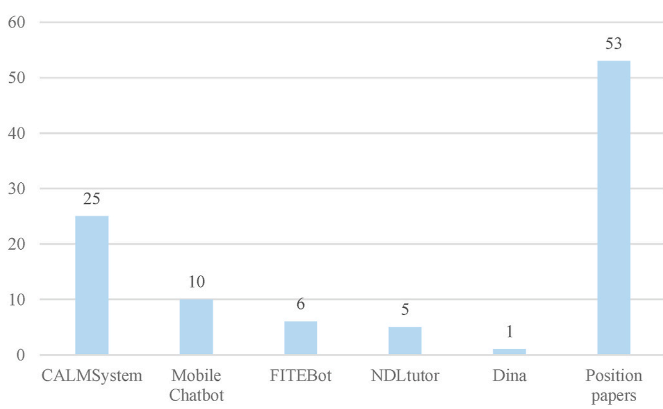

Fig. 9. Data distribution of the types of chatbots adopted in the articles.

Table 3
Percentage of research designs in each period.

Research designs	2003–2009 (N = 11)	2010–2015 (N = 8)	2016–2020 (N = 81)	2003–2020 (N = 100)
Analytical: System design and analysis	64%	38%	28%	33%
Experimental methods	9%	25%	23%	22%
Position paper	18%	0%	19%	17%
Non-experimental (Survey)	9%	38%	11%	13%
Qualitative methods	0%	0%	7%	6%
Mixed methods	0%	0%	11%	9%

findings revealed that only a few types of chatbots have been adopted in human behavior research.

4.5. Research designs and analysis methods

Table 3 shows the distribution of research designs for each period. This study found that the research on chatbots predominantly used an analytical system design (33%), followed by experimental methods (22%), position papers (17%), and survey methods (13%) (Table 3). Between 2003 and 2009, many researchers used an analytical system design to discuss the chatbot system development and design questionnaire surveys; they also collected and analyzed data to answer the research questions. In the recent 10 years, although the number of papers on experimental and survey methods increased sharply, the majority are still system design and analysis contributions. For instance, Tsai et al. (2020) used a conversation-based building inspection support system with data visualization and support management decision making functions to improve the accuracy of quality budget allocation and to reduce the paperwork process loading and management problems. Casillo et al. (2020) built a recommender system for adaptive tourist routes to show the most important cultural sites in line with tourists' needs. These studies showed that chatbot technology has matured, and researchers have begun to consider how to improve the intelligence of chatbots and customize the application of chatbot development and successful models.

Table 4
Percentage of analysis methods used in each period.

Analysis methods	2003–2009 (N = 11)	2010–2015 (N = 8)	2016–2020 (N = 81)	2003–2020 (N = 100)
Descriptive statistics	9%	13%	19%	17%
ANOVA/Mixed multivariate analysis of covariance (MANCOVA)	0%	25%	12%	12%
PLS, structural equation modeling (SEM)	0%	13%	6%	6%
t-test	9%	13%	5%	6%
Bivariate Correlations	0%	0%	5%	4%
Interviews	0%	0%	2%	2%
Chi-square tests	0%	0%	1%	1%
Confirmatory Factor Analysis.	0%	0%	1%	1%
Mann–Whitney's *U* test	0%	0%	1%	1%
Others (Position paper and Analytical)	82%	38%	47%	50%

Table 4 shows the distribution of statistical methods; most of the studies used descriptive analysis (17%), ANOVA/mixed multivariate analysis of covariance (MANCOVA) (12%), *t* tests (6%), Partial Least Squares (PLS), structural equation modeling (SEM) (6%), and interviews (2%) to test their research results. Many studies also used chi-square tests/logistic regression/bivariate correlation confirmatory factor analysis, the Mann-Whitney *U* test, and other analysis methods. The results showed that position papers and analytical system design (50%) researchers advanced the development and application research of chatbot systems.

This study also examined the statistical methods used in chatbot research, and identified three stages. More than half of the studies were published between 2003 and 2009; these were position papers or studies that used analytical design methods. In the 2010–2015 stage, ANOVA/MANCOVA analyses were added. In the 2016–2020 stage, many researchers chose descriptive statistics as their analysis method. For example, Stoeckli et al. (2019) compared the 14 lower-level affordances and 14 constraints of enterprises' chatbots. The authors concluded that GUI elements could reduce the relatively high actualization effort; thus, chatbot development should consider the affordance-related dependencies between individual users, regardless of whether chatbots are used. In addition, a growing number of studies involved health counseling applications; for example, Piau et al. (2019) developed a smartphone chatbot to optimize the monitoring of older patients with cancer. Other studies pointed out that chatbots could be used to help people realize the benefits of managing their own health (Poncette et al., 2020).

4.6. Top 10 most productive authors

Table 5 shows the contributed scores and determines the top 10 authors based on the citation frequency of the journal articles used in the

Table 5
Rankings of the top 10 highly cited authors (2013–2018).

	2003–2007		2008–2011		2012–2016		2017–2000		All	
	Author	Score	Author	Score	Author	Score	Author	Score	Author	Score
1	Kerly, A	94	Jia, JY	100	Coniam, D	100	Fryer, LK	185	Fryer, LK	185
2	Tatai, G	80	Burden, DJH	100	Allison, D	100	Ford, H	132	Kerly, A	141
3	Abu Shawar, B	60	Hsieh, SW	100	Reshmi, S	60	Chan, HY	132	Ford, H	132
4	Csordas, A	54	Kerly, A	47	Griol, D	60	Mou, Y	107	Chan, HY	132
5	Bull, S	53	Lee, C	42	Hill, J	47	Araujo, T	100	Mou, Y	107
6	Atwell, E	40	Pirrone, R	42	Lorenzo, CM	47	Tseng, JJ	100	Jia, JY	100
7	Lu, CH	38	Crutzen, R	38	Balakrishnan, K	40	Natale, S	100	Burden, DJH	100
8	Szalo, A	35	Ellis, R	32	Callejas, Z	40	Powell, J	100	Hsieh, SW	100
9	Hall, P	32	Jung, S	28	Sundar, SS	38	Morelli, M	100	Allison, D	100
10	Chiou, GF	26	Russo, G	28	Ward, T	37	Liu, BJ	60	Coniam, D	100

research and the ranking of the authors. Between 2003 and 2007, the most productive researchers came from English-speaking countries. During this period, the researchers showed a greater interest in bringing chatbots into education to promote learning. Between 2008 and 2011, the researchers were mainly from English-speaking countries and Asian countries. The researchers were interested in providing computer technology, such as Jia (2009) and Huang et al. (2020), to provide full support to students' online learning. CSIEC (Computer Simulation in Educational Communication) is a computer-assisted English learning chatbot based on text knowledge and reasoning. Between 2012 and 2016, the researchers came mainly from Hong Kong. For example, Coniam (2014) evaluated the language accuracy and usability of app chatbots from an English as a Second Language (ESL) perspective. Finally, between 2017 and 2020, the researchers came mainly from Hong Kong and focused on the advantages of teaching through action and conducting experiments. For example, Fryer et al. (2017) conducted experiments to compare the tasks with different partners (Chatbot and Human): they combined design time experience with a chatbot system to observe and monitor students' learning behavior in language courses and thus verify the benefits of a chatbot system in education. The research method chosen by the authors changed from a single chatbot implementation to a comparison of different experimental designs. In addition, the analysis method changed from descriptive analysis to various statistical methods.

5. Discussion and conclusion

Highly cited papers are considered to represent useful and high-quality potential indicators for follow-up research (Cheng et al., 2020; Lai, 2020). By analyzing the highly cited papers, the advantages of the research related to human behavior that has attracted widespread attention can be used to make suggestions for future research. An analysis of the top 100 highly cited papers showed that chatbots have been applied to topics and issues that have been rarely investigated and analyzed. In terms of the research methods, the analysis showed that papers published between 2003 and 2009 tended to be analytical system design or research design articles; from 2010 to 2015, the research design was based on nonexperimental survey methods. Between 2016 and 2020, many chatbot research articles were produced, but only a few scholars, such as Riikkinen, Saarijärvi, Sarlin, & Lähteenmäki, 2018, used mixed and qualitative methods such as qualitative interviews to analyze the value of AI-based chatbots for users.

Regarding the application field, although a significant amount of the chatbot research discussed the effectiveness of chatbots in different areas, the high citation rates found for the first 100 articles showed that many of the studies using chatbots were biased toward the computer science information systems, AI, and medical informatics fields. Additionally, the research in various fields has not been discussed in depth. For example, only 11 of the top 100 articles were published in educational research, which showed that, although education researchers have begun to pay attention to the research and analysis of chatbots in education, more research is needed in this field. In addition, only five of the top 100 cited articles were directly related to education (i.e., language learning), which means that there is space for conducting chatbots in human behavior studies from the perspective of educational technology in the future.

In terms of statistical methods, a few studies reported the results of the chi-square test, but they often performed descriptive statistics and ANOVA/MANCOVA in their research. According to the results, the most productive authors tended to adopt various statistical methods and attract the attention of researchers. In addition, the statistical methods used by previous studies might help us to answer the question investigated in this study. In this study, 33% of the highly cited papers used analytical system designs to prove the research hypothesis, especially between 2003 and 2009, while 68% of the papers published used an analytical system design. From 2010 to 2015, the research design began to incorporate ANOVA/MANCOVA. For example, Fulmer et al. (2018) used MANCOVA to analyze psychological AI to relieve symptoms of depression and anxiety.

Finally, the publications from 2003 to 2007 shown in this study were not the earliest published works with high citation rates. The research conducted by Hill et al. (2015) examined real conversations with AI, and compared human–human online conversations and human–chatbot conversations. Therefore, it is recommended that in future research, a comprehensive analysis of the author's productivity can be used as an indicator, such as the equal contribution standard (EC), the indicated contribution percentage method (PCI), h-index, and Google Scholar (Cheng et al., 2020; Lai, 2020). In addition, future studies could conduct a large-scale review using papers with higher citation rates and include newer research for a more comprehensive review.

Based on the top 100 cited papers, this study proposes potential directions for future research. Most of the highly cited chatbot research was published between 2000 and 2016. The analysis showed that the researchers compared different chatbot systems to develop more effective chatbot application methods. In addition, the most frequently cited papers introduced and verified methods of system development, transformed chatbots from entertainment to form a part of the living environment, and developed human–computer interaction learning. The amount of chatbot research conducted abroad has also increased. The results could be used by novice researchers to improve chatbot learning research.

Our literature review has identified that there is still room for applications of chatbots in education research. The findings in this article highlight research gaps and propose future research directions in this field. The results of this article show that chatbots are still in the early stages of being implemented in the field of education. Therefore, future research should focus on the added value of chatbots and apply them to educational research to compare the differences between chatbot learning and other traditional learning methods. Additionally, although a few studies have shown the potential of chatbots to improve students' learning process and outcomes, the existing empirical research has rarely discussed the use of chatbots in the teaching of K-12 subjects as well as the impacts of using chatbots on learners' higher order thinking and learning behaviors, which could be good research topics for future studies. It is also suggested that researchers analyze the teachers' and learners' perceptions of using chatbots to teach and learn from different angles, such as analyzing their drawings regarding the concept of using chatbots in school settings. Moreover, it is also important to examine the effects of using chatbots on the performances and perceptions of teachers and students with different personal factors, such as technology use experience, confidence in using chatbots, and cognitive styles.

6. Conflicts of interest and source of funding

The author would like to declare that there is no conflict of interest in this study. This study was a retrospective bibliometric analysis focusing on analyzing the published articles. No clinical trials were conducted in this study. Approval from an institutional review board was not applicable.

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