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PERSONALISED CONVERSATIONAL AGENTS: A SYSTEMATIC REVIEW

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Abstract

The purpose of this article is to discuss the inconsistency responses in generative personalised conversational agents and identifies future research opportunities. The study employed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to analyze 257 papers from databases like Scopus, Web of Science, and Cornell University database library from 2000 to 2022. The selected articles focused on computer science and information technology, emphasizing full papers and conference contributions published in English. This study found out series of solutions to inconsistency responses in personalisation conversational agents. However prompt tuning and copy technique generate more consistent and relevant responses. Among the popular corpora for training and evaluation were Persona-Chat, Personal-Dialog, and ConvAI2. The results revealed that China leads in research experience related to neural-based personalised conversation tools in publications during 2021. Researchers can leverage these insights to improve existing conversational models and develop more effective artificial intelligence systems.

Key terms: Generative models, information retrieval, persona-based conversational agents, prisma, unstructured datasets.

1.0 INTRODUCTION

Generative personalised conversational agents are not a perfect model, as they sometimes generate inappropriate, irrelevant, or absurd responses (Papangelis et al., 2021; Liu et al., 2022). Therefore, this paper focuses on what exactly is the solution to inconsistency in personalised conversational agents. The study employed Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework and provide some research directions.

Generative Models

To alleviate the inconsistency response generated by the encoder-decoder model, one possible solution to many researchers is to incorporate user's interests knowledge into conversational agents, known as personalized conversational agents. Rather than relying on predefined responses, the generative models generate new responses from scratch by conditioning on the dialogue history and external knowledge (Ma et al., 2021). Figure 1 depicts the structure of generative models consisting of dialogue and knowledge encoding, knowledge selection and response generation.

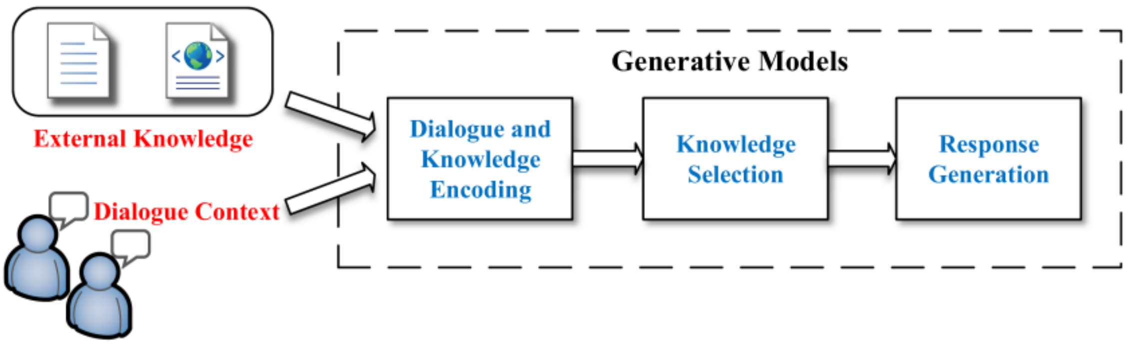

Figure 1: Generative Models

Structure of Generative Models Ma et al. (2021) by creating a database to store some of the data to reply to queries, the dialogue and knowledge encoding mapped discrete symbols to continuous vectors (e.g. sequence-to-sequence model). Knowledge selection, a mechanism that manipulate existing knowledge e.g. knowledge graph with inference techniques like integer linear programming while response generation generate a system response.

In the dialogue and knowledge encoding, the generative model like encoder-decoder or transformers, first encodes the entire dialogue history into a fixed-length vector representation. For the knowledge selection, the dialogue history and external knowledge encodings are combined into a memory network framework Ma et al., (2021) with an attention mechanism. The response generation takes the results of previous modules (Dialogue and knowledge encoding and Knowledge Selection) as input and generates the final dialogue response using natural language generation techniques such as language modeling or sequence-to-sequence models. This knowledge could be persona-based, knowledge grounding or emotional intelligence.

Information Retrieval

Information-retrieval systems generate responses by retrieving pre-existing responses from a database or corpus. These responses are selected based on how closely they match the user's input. Response by retrieval systems is commonly used in customer service chatbots, where they can provide quick and accurate answers to frequently asked questions (Ma et al., 2021; Gao et al., 2019). A typical information-retrieval architecture is shown in Figure 2, composed of three modules: fusion, matching and ranking.

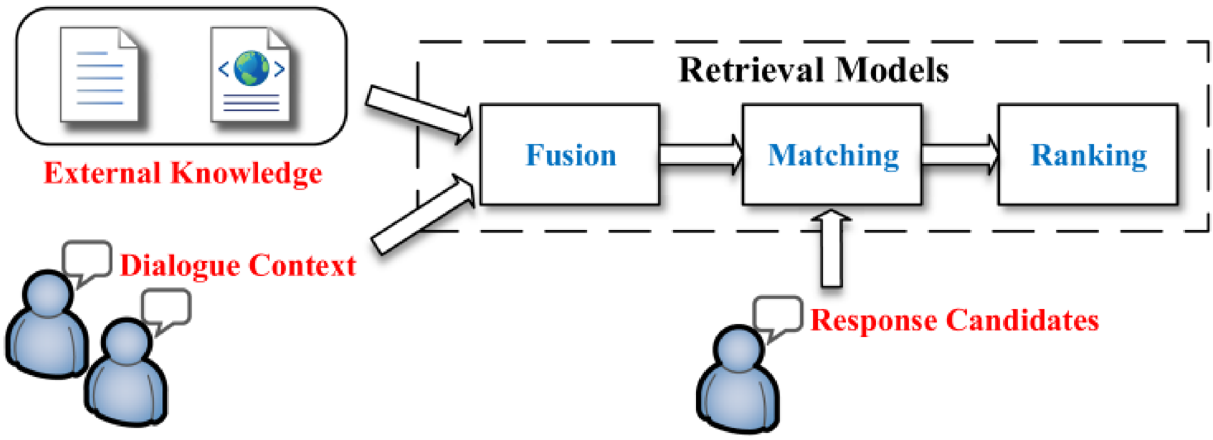

Figure 2: Retrieval-based Conversational Agents

Retrieval-based Conversational Agents Architecture (Ma et al., 2021). It shows the process of retrieval augmented generation. Creating a database to store some of the data to reply to queries. The fusion provides similar vectors. The matching module identify the relevant documents while ranking module ordering relevant documents based on their relevance to the query.

Fusion refers to the process of combining the results of multiple retrieval models to improve the overall retrieval performance. In the case of matching module, it is responsible for identifying the relevant documents based on the query while ranking module is responsible for ordering the relevant documents based on their relevance to the query.

Persona-based Conversational Agents

Personalisation of conversational systems incorporate the persona of the user as embeddings with the dialogue history Tejwani et al. (2020) or modify the input sequence to include the attribute description while training such as personal profile. Table 1 elicit persona definition from different sources.

Table 1: Definition of Persona Agents

Source	Definitions
Li et al. (2016)	As the character that an artificial agent, as actor, plays or performs during conversational interactions" A persona is made of different elements of identity like background facts or user profile, language behavior and interaction style.
Qian et al. (2017)	The personality of a chatbot refers to the character that the bot plays or performs during conversational interactions.
Kottur et al. (2017)	Persona is considered as the speaker-addressee model of Li et al., 2016
Zheng et al. (2018)	Persona is a profile that are natural and descriptive, termed profile to be multiple sentences of textual description.

Mazare et al. (2018)	The persona is a set of sentences representing the personality of the responding agent.
Song et al. (2019)	Follow the definition of persona in (Mazare et al., 2018).
Wolf et al. (2019)	It is a few sentences describing who it is.
Zheng et al. (2019)	The persona of a speaker can be viewed as a composite of diversified personality traits.
Liu et al. (2022)	Persona is any type of profile containing personal information about a conversational partner that offers context allowing for better understanding of a speaker's meaning/intent or facilitating more appropriate phrasing to improve the likelihood that a speaker's dialogue partner will be more receptive to the information being conveyed.

Persona Agents definition identified from different sources in the systematic review. User features that enhanced persona-based conversational agents were analyzed as follows:

Character and Personality

Character and personality refer to the attributes and traits assigned to the virtual agent to make it more engaging and relatable to users. The character of a persona-based conversational agent defines its identity and role while personality refers to the set of traits and qualities that determine how the persona-based conversational agent behaves and interacts with users (Kim et al., 2019).

Conversational Style

Deborah Tannen's theory according to Shamekhi et al. (2016); Hoegen et al. (2019); Aneja et al. (2021), is the most widely used framework for understanding human conversational style. They define conversational style as the way people convey meaning beyond the content of their words in ordinary conversation. In conversation, style can be influenced by several factors, including personality, cultural background and word choice. As in lexical entrainment, which has been observed in human-agent (Li et al., 2016; Qian et al., 2017; Kottur et al., 2017; Zheng et al., 2018) interactions. The first to try into this direction for persona-based conversational agents is (Li et al., 2016). The speaker model is proposed to encode persona in dense vector, capture the speaker characteristics such as personal information and speaking styles.

User Engagement

In human-machine interaction Oertel et al. (2020), engagement enable sophisticated interfaces capable of adapting to users. One of the utmost importance is to personalise its interactions with users based on their individual preferences and interests. One area an agent can use to maintain engagement according to (Battaglino et al., 2015) is through conversational storytelling. In the study, they developed an exercise trainer agent to tell conversational stories that influence the storyteller's health counselling behaviour with the user.

To increase user's engagement Shamekhi et al. (2016), virtual agents involving chit-chat are classified into two categories; implicit model, learnt user's persona implicitly from the dialogue data, represented as the user's spoken utterance embedding. Secondly, explicit model, virtual agents generate response explicitly conditioned either on a given profile with various attributes (Zheng et al., 2020; Wolf et al., 2019) or on a text-described persona (Zheng et al., 2018). The challenge with these methods is maintaining consistency between two speakers. Table 2 presents the difference between the virtual agent's classifications.

Table 2: Classification of Persona Virtual Agents

Features	**Implicit Persona**	**Explicit Persona**
Persona representation	It uses dialogue history or semantic vectors.	It uses predefined attributes or text profile.
Inference	Leverage dialogue history embedding with the generative models. Clustering or link prediction to discover the persona of the speaker from the dialogue history or the knowledge base.	Conditioning the dialogue model on the given persona (text profile) using retrieval-based methods.
Advantages	It enhances dialogue consistency and naturalness.	It improves user satisfaction and engagement.
Disadvantages	It generates irrelevant or contradictory responses if the dialogue history is noisy or incomplete.	It requires more data and resources to create and maintain the persona profile.
Note: Comparison of Implicit and Explicit Persona-based Conversational Agents		

The study further identifies the following limitations of persona-based conversational agents from (Liu et al., 2022).

- Lack of data, both annotated and unannotated, as real conversations are still not widely available for different domains and languages.
- Unstable quality of the generated responses remains a challenging issue for many generation-based models.
- It is still a challenging task to evaluate the free-form responses from the generation-based methods, especially in terms of personalization.

Unstructured Dataset

Unstructured dataset such as text document, social post, images can be collected from machine-to-machine, human-to-machine, and human-to-human (Tran, 2021). Table 3 presents some human-to-human datasets found in the literature for conversational agents and persona-based conversational agents into two types: (1) Single-turn which based on immediately preceding utterance and (2) Multi-turn based on multiple previous utterance as well as a user query.

Table 3: Dataset for Conversational Agents

General Conversational Agents Datasets	Single-Turn	Multi-Turn
		Cornell Movie Dialogs Corpus https://www.cs.cornell.edu/~cristian/Cornell_Movie-Dialog_Corpus.html
	Movie Dialogue Corpus https://www.kaggle.com/datasets/Cornell-University/movie-dialog-corpus	Ubuntu Dialogue Corpus https://github.com/rkadlec/ubuntu-ranking-dataset-creator
	Stack Exchange question-answering community dataset https://github.com/brmson/dataset-factoid-webquestions	OpenSubtitles Corpus http://opus.nlpl.eu/OpenSubtitles-v2018.php
	Chinese dialog corpus from Baidu Tieba (Chinese online forum) https://bitbucket.org/comp551proj1/proj1	Friends" and "The Big Bang Theory" TV show dialogue datasets https://www.kaggle.com/datasets/shilpibhattacharyya/the-big-bang-theory-dataset
		MovieChAtt dataset https://github.com/yuyuz/MetaQA
	Weibo dataset (Chinese microblog website)	Switchboard Corpus https://nlpprogress.com/english/dialogue.html
		The American TV series "Friends" https://github.com/anabazzan/friends
		DailyDialog dataset http://yanran.li/dailydialog
		Reddit Conversation Corpus https://paperwithcode.com/dataset/reddit-conversation.corpus

Persona datasets Dialogue NLI	Persona-Chat https://gitHub-datasets-mila/datasets-personachat
	PersonalDialog https://github.com/silverriver/PersonalDialog
	KvPI https://github.com/songhaoyu/KvPI
	ConvAI2 https://parl.ai/projects/convai2
	Dialogue NLI https://github.com/soroushjavdan/NLIbert

One key difference between general conversational agents dataset and persona-based conversational agents dataset is that, the latter includes dialogues where interlocutors have predefined personas with annotated characteristics such as speaker consistency and personality response while the former does not explicitly include annotated persona for each dialogue but covers a wide range of topics.

The study presented in this paper conducted a systematic review of personalised conversational agents. The primary objective was to find out the solution to inconsistency responses in generative personalised conversational agents and identify potential areas for future research. To achieve this, the study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. The rest of this article is organized as follows: section 2 provides literature review, section 3 describes the methodology, section 4 presents results and discussion, and we conclude the paper in section 5.

2.0 LITERATURE REVIEW

Authors in Gao et al. (2019) work on neural approaches to conversational artificial intelligence. The authors distinguished neural and traditional approaches to conversational AI and challenges being faced. Sodoc et al. (2019) survey available corpora for building data-driven dialogue systems. Huang et al. (2019) reviewed challenges in building intelligent open-domain dialogue systems. Sun et al. (2019) categorised and discussed the generation methods in open domain conversational agents as well as their advantages and disadvantages. Allouch et al. (2019) described areas in which conversational agents were successful along with their goals, technologies, vision and challenges. Caldarini et al. (2022) provided a survey of recent advances in chatbots for instance, transformer. Yan et al. (2022) survey chit-chat systems from two perspective: techniques to build chit-chat systems and chit-chat components in completing information retrieval tasks. Ni et al. (2022) comprehensively reviews state-of-the-art research outcomes in dialogue systems and analyses them from two angles: model type and system type. Conversational agents in health care were proposed in Kocaballi et al. (2019) to understand ways in which personalization has been used with conversational agents in health care. Ma et al. (2021) made comparison between unstructured text enhanced dialogue system (UTEDS) and traditional data-driven approach. Additionally, a reviewed of the current state of the art in personalisation conversational agents were proposed in (Liu et al., 2022). They conducted experiment on existing dataset, ConvA12, to study response retrieval performance with and without personas using Poly-Encoder and Ranking Profile Memory Network.

3.0 METHODOLOGY

This section describes the methodology. The study follows Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol of conducting systematic reviews, which consist of a 27-item checklist and a four-phase flow diagram (see Figure 3). This protocol was developed in the medical field by a group of 29 scholars according to (Pahlevan-sharif et al., 2019), with the intent to increase the transparency and accuracy of literature reviews. The choice of PRISMA over other existing protocols lies in the recognition of its comprehensiveness, its use in several disciplines worldwide and its potential to increase consistency across reviews.

Data Gathering

The study utilized Scopus, Web of Science and Cornell University database library to identify relevant literature. For instance, the data were obtained from SCOPUS on 25th May, 2022. The search terms used were "personalized dialogue agents". This is an example of a Boolean search in Scopus; "personalized dialogue agents" AND (LIMIT- TO (PUBSTAGE, "final")) AND (LIMIT TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE,"ar")) AND (LIMIT-TO (SUBJAREA, "comp")) AND (LIMIT-TO (LANGUAGE, "English")). This command explores article title, abstract, keyword of every published document in the selected field and exported to Microsoft (MS) excel spreadsheet. The exported paper was pilot tested by one reviewer to screen the abstract. A column is created in MS excel spreadsheet to indicate which paper to include or not, given the range as; *not include = 0, include = 1, and maybe = 2*. The following eligibility criteria is defined to select the full-length paper: Articles must be original paper and conference paper, The article must be in English Language and from the field of Computer Science, Extracted articles were published between 2000 to 2022, The articles must be unstructured text-based Neural personalised conversational agents, The search focused on all the country suggested by the system from China, United States, Canada, India, and others.

Article Filtering and Reviewing

The authors read through each article title and abstract individually using the eligibility criteria defined to select relevant papers to be included. Then, later downloaded the full text of the studies remained and carefully review them to identify those that should be excluded or filtered according to the eligibility criteria. Thus, a total of 257 records were extracted at this stage. The PRISMA flow diagram showing the different steps of the study selection (that is, included, eligibility, screening and identification), number of studies identified, number of excluded papers is presented in Figure 3.

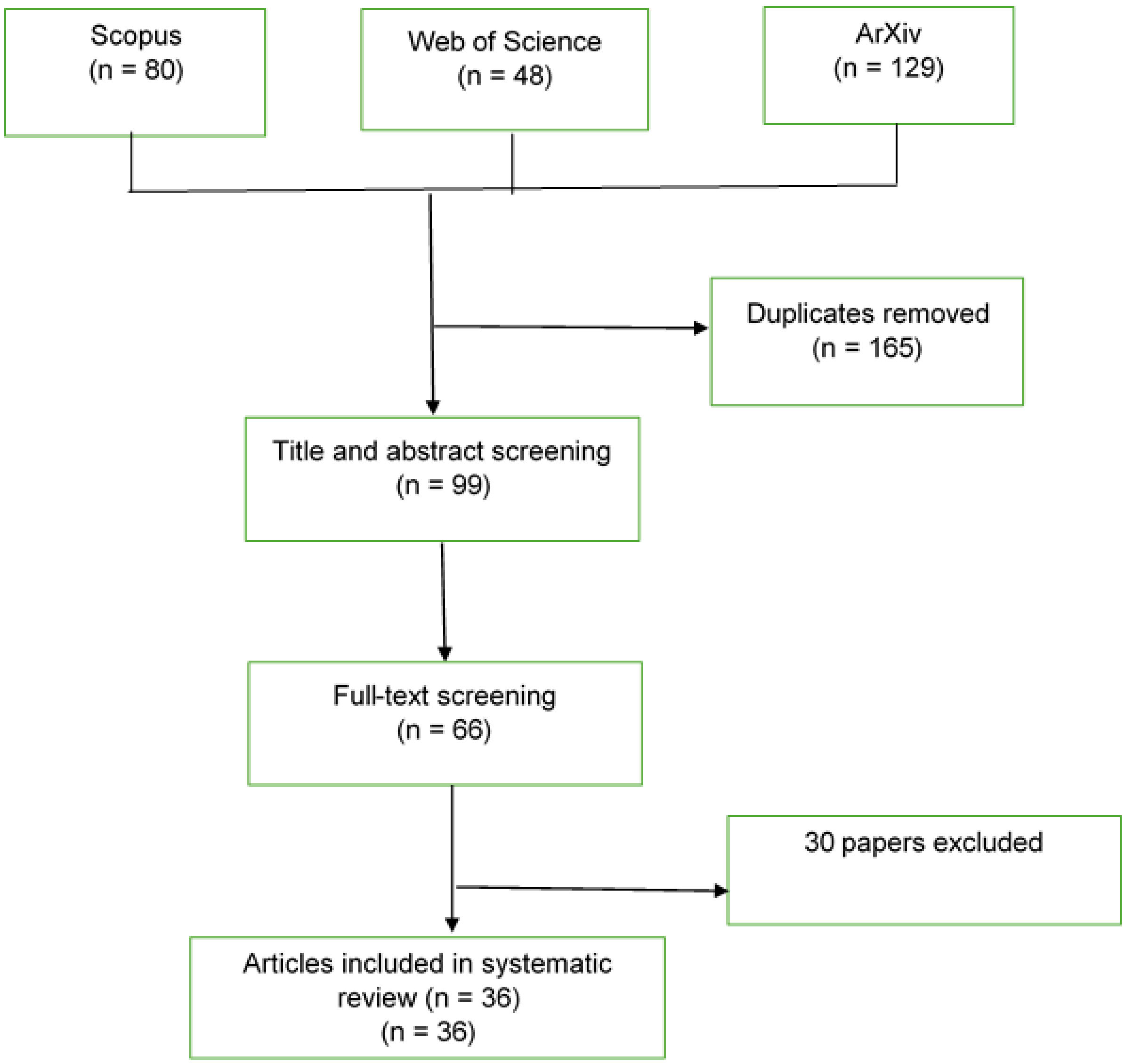

Figure 3: PRISMA Flow Diagram

Note: Flow diagram of included studies identified from 3 databases search. It presents the included, eligibility, screening, identification and excluded papers identified in the study.

4.0 FINDINGS AND DISCUSSION

The study presents the main results from the systematic literature review using descriptive analysis.

Descriptive Analysis

Descriptive analysis of systematic review presents the results of the studies included in the review which include the following elements:

- Distribution of articles base on year and databases
- Distribution of article base on country

Distribution of Articles Base on Year and Databases

Figure 4 shows the publications per year result of the studies included in the review, yielding 36 results from the three databases. The year 2020 (8 publications) and 2021 (11 publications) received the most significant publications.

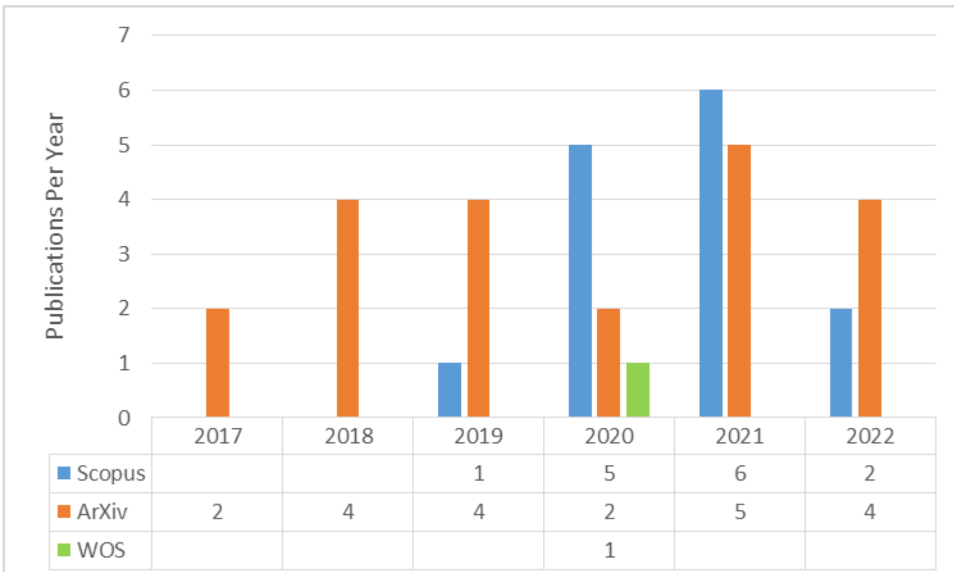

Figure 4: Distribution of articles base on year and databases

Distribution of Articles Base on Country

Figure 5 shows the best countries with research experience in using neural-based personalized conversation tools, with China (21) leading the way.

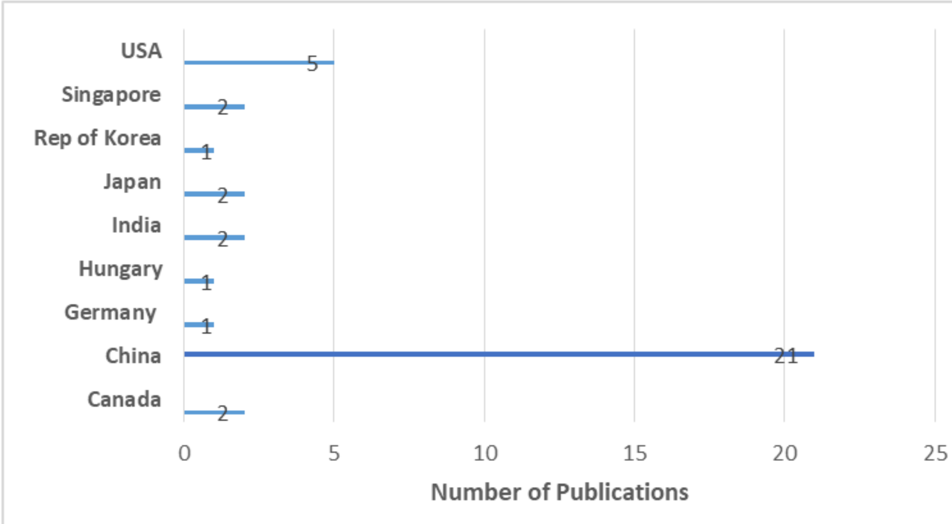

Figure 5: Distribution of articles base on Country

It depicts best countries with research in neural-based personalized conversational agents with China leading the way. Table 4 presents some of the affiliations in China that engaged in personalized conversational agents research with Hong Kong University of Science and Technology having (6 publications) and (4 publications) each with Harbin Institute of Technology and Renmin University of China.

Table 4: Affiliation in the articles included in the study

Affiliations	**No of Articles**
Hong Kong University of Science and Technology, China	6
Beihang University, Beijing, China	1
Harbin Institute of Technology, China	4
Tsinghua University Beijing, China	1
Pekin University, China	1
Beijing Institute of Technology, China	2
University of Science and Technology Hefei, China	1
Shandong University, China	1
Renmin University of China	4

Leading Affiliation in Personalized Conversational Agents in the articles included in the study

Discussion

Methods to address inconsistency in personalised conversational agents are conditioning on dialogue context, incorporating personality into decoding process, inferring agent personality, adapted Model-Agnostic Meta-Learning, sequential decoding fusion, latent distribution conditioning, prompt tuning and copy technique. Study has shown that these methods enhance user experience, increase system reliability, and pave the way for natural context-aware interactions. Therefore, researchers can leverage these insights to create more sophisticated and user-friendly chatbots.

5.0 CONCLUSIONS AND RECOMMENDATION

Conclusions: The study conducted a systematic review of personalised conversational agents involving 257 papers from databases like Scopus, Web of Science, and Cornell University database library from 2000 to 2022. The study highlighted various approaches to addressing inconsistent responses in personalised conversational agents. The results revealed that China leads in research experience related to neural-based personalised conversation tools, while African countries lag in this area.

Recommendation: Consequently, there is an urgent need for African researchers to explore this field, particularly by developing conversational agents in their native languages.

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