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Experimentation for Chatbot Usability Evaluation: A Secondary Study

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ABSTRACT Interest in chatbot development is on the rise. As a usability evaluation is an essential step in chatbot development, the number of experimental studies on chatbot usability has grown as well. As a result, we think a systematic mapping study is opportune. We analyzed more than 700 sources and retrieved 28 primary studies. By aggregating the research questions and examining the characteristics and metrics used to evaluate the usability of chatbots in experiments, it is possible to identify the state of the art in chatbot usability experimentation. We conducted a systematic mapping study to identify the research questions, characteristics, and metrics used to evaluate the usability of chatbots in experiments. Most experiments adopted a within-subjects design. On the other hand, few experiments provided raw data, and only one of the identified papers was part of a family of experiments. Effectiveness, efficiency, and satisfaction are usability characteristics used to identify how well users can learn and use chatbots to achieve their goals and how satisfied users are during the interaction. Generally, the experimental results revealed that chatbots have several advantages (e.g., they provide a real-time response and they improve ease of use) and some shortcomings (e.g., natural language processing, which is rated as the weakness most in need of improvement). This research offers an overview of chatbot usability experimentation. The increasing interest in this area is very recent, as works did not start to be published until 2018. Chatbot usability experiments should be more replicable to improve the reliability and transparency of the experimental results.

INDEX TERMS Usability, chatbots, experiments, family of experiments, systematic mapping study.

I. INTRODUCTION

A chatbot, also known as chatterbot, is domain-specific textbased software that supports human users with specific services [1], [2]. Joseph Weizenbaum developed the first dialog system (ELIZA) in the 1960s. ELIZA is considered to be the first chatbot [3]. Remarkable advances in deep learning, natural language (NL) processing, and machine learning are causing a seismic shift. Thus, chatbots are now better at interpreting a natural language phrase by the user and sending back the response in a similar way to users [4]. In turn, this has created unlimited possibilities and productive and useful experiences based on chatbots that can

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access and interact with digital services in many different applications [3], [5], [6].

In the current on-demand, real-time world, users expect the information they want to be only a click away. Chatbots have always played the role of information or service provider, especially in the e-commerce business world [4]. In recent years, chatbots have been pervasive, as e-commerce demand (e.g., online consulting, online payment) has grown and barriers to chatbot creation (like advanced technical expertise) have receded. People can create their own chatbot on social media platforms like Facebook Messenger, Twitter, and WeChat without sophisticated programming knowledge and other highly specialized technical skills. Some sites, like ChatBot (chatbot.com) or appypie (appypie.com/chatbot/builder), help novices develop simple chatbots using drag-and-drop interfaces.

Currently, chatbots are being applied in a range of different contexts, where they (i) help TV viewers interact with their TVs [7], (ii) recommend music [8], and (iii) perform collaborative modeling as part of the software development process [9]. In other words, chatbots have more or less infinite applications in many fields aimed at facilitating interaction. We are interested in exploring the state of the art of experimentation to evaluate chatbot usability. Therefore, our research does not place any limits on the context of use, since chatbots can potentially exist in any area.

Not all users are ready to place their trust in chatbots in preference to other communication channels, like email, due to their perceived poor understanding and quality of response [10]. In this context, the chatbot is still far from reading users' minds. Therefore, it is necessary for better integration between usability evaluation and the chatbot [11].

Usability evaluation, a growing field that is still being defined, refers to how well users can learn and use software to meet their requirements and addresses how satisfied users are during the process [12]. In software engineering (SE), usability is commonly considered to be one of many non-functional requirements and quality characteristics [13], where it has come to be recognized as a crucial tool for success in the competitive commercial world [14]. The right choice of evaluation methodology must be applied for the current research question or issue [12]. Apparently, chatbot usability evaluation is not yet a mature field [11].

In general, a chatbot usability evaluation learns and borrows experience from experimentation in software engineering (ESE). In order to explore chatbot usability experimentation, we conducted a preliminary survey, which failed to find any previous studies or literature reviews providing a consolidated view. As a result, we conducted a systematic mapping study (SMS) with the aim of: (i) exploring the state-of-the-art on chatbot usability experimentation, (ii) identifying the research questions that were investigated in experiments about chatbot usability, and (iii) defining the metrics used in experiments to measure chatbot usability in SE. Finally, our findings address the research questions and topics raised in this research in order to pinpoint the topics requiring future work. This research provides an informative review of the status quo of chatbot usability experimentation. Our contribution is designed to provide a map of everything that has been published, since we included all reported references in the literature of our SMS on chatbot usability experimentation. This map includes the usability characteristics used to measure the results and the categorization of the metrics used to evaluate the experimental results, the sample size of the experiment, the types of subjects participating in the experiment, the experimental design and procedure, the implemented tasks of the experiment, measurement instruments and statistical techniques, as well as any replications carried out. With this information, researchers interested in conducting experiments and/or replications related to chatbot usability will have access to a baseline accounting for all the aspects that they should consider (such as experimental design). Our research is a practical step towards a better understanding of chatbot usability experimentation, and its primary audience is researchers in the areas of human-computer interaction (HCI), SE, and chatbot development.

The paper is organized as follows. Section 2 outlines the main concepts of usability, and related work about chatbot usability evaluations and families of experiments. In Section 3, we explain the research method, the research questions of our study and the search strategies that were used in this article. In Section 4, we present the answers to each of the research questions. Section 5 provides a discussion of the results. We discuss the threats to validity of this study in Section 6. Finally, we outline the conclusions of our study and future work in Section 7.

II. BACKGROUND

To conduct the SMS, we referred back to a baseline study [11]. Ren *et al.* [11] found that chatbots and their respective usability evaluation were popular topics by 2015. This was when the number of publications started to grow, and many articles have been published every year since then. However, findings with respect to the ideal usability experiment were inconclusive in [11].

A. CHATBOT USABILITY EVALUATIONS

Usability is a common concern in SE. The International Organization for Standardization ISO 9241-11:1998 put forward a generalized definition of usability as *''the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use''* [15]. The ISO/IEC 25010:2011 software quality model categorized usability as a sub-characteristic of system/software product quality properties. It was defined as a subset of quality in use consisting of effectiveness, efficiency, and satisfaction, for consistency with its established meaning [16].

Below we review and explore the differences between the five existing research papers on the usability aspects of chatbots [17]–[22] and our research.

Abd-Alrazaq *et al.* [17] discussed the technical metrics used to evaluate healthcare chatbots. They started by describing the 65 studies that they included addressing detailed features (e.g., study design). They then categorized the technical metrics used to measure healthcare chatbots into four groups: global metrics, metrics related to response generation, metrics related to response understanding, and metrics related to esthetics. Their scoping review findings show that usability is the most commonly assessed aspect of healthcare chatbots.

Hobert [18] conducted a literature review to investigate which methods are suited for evaluating pedagogical chatbots in interdisciplinary research domains. While they declared 25 papers as the case base, they did not detail the number of papers that were left at the end of each screening process. Their findings revealed that many different evaluation

approaches were adopted in research on educational conversational agents. Besides, they pointed out that researchers tended to analyze specific aspects in terms of their discipline. They concluded that comprehensive evaluations that analyzed pedagogical conversational agents from different perspectives were usually missing. They suggested that future research needs to test whether evaluating multiple goals in one research study is practicable and provides adequate contributions.

Rapp *et al.* [19] conducted a systematic literature review on how users interact with text-based chatbots. After applying the grounded theory literature review method on three electronic databases, they included 83 studies published from 2010 to 2020 in the review. They firstly discussed the features of the identified research in terms of publication venues, research methodologies, and chatbot characteristics. They concluded that experiments were the most commonly used methods to evaluate text-based chatbots. Secondly, they described the themes (e.g., chatbot user experience (UX)) and sub-themes. Note that although usability and UX have a lot in common, UX may be seen as an extension of usability. They singled out five main research themes in 83 studies. They then analyzed and identified the main methodological methods used in these papers.

Following the phenomenological method and Cooper's taxonomy of literature reviews, Tariverdiyeva and Borsci [20] conducted a literature review to explore aspects that influence a user's perception of the chatbot. They proposed a list of 27 key factors that affect users' perceptions of usability, including, but not limited to, response time, perceived ease of use, user privacy and ethical decision making.

To comprehensively review the quality attributes of chatbots and identify appropriate quality assurance approaches, Radziwill and Benton [21] conducted a literature review covering 32 conference papers and 10 journal articles. They outlined the quality attributes organized in terms of efficiency, effectiveness and satisfaction according to the concept of usability. Based on the analytic hierarchy process, they then synthesized the approaches across primary studies to recommend a compound technique.

In the knowledge that voice-based conversational agents had advanced over recent years and voice-related publications had increased correspondingly over the last 5 years, Seaborn and Urakami [22] conducted a rapid review of quantitatively measured voice-based system (including chatbot) UX through experiments. After reviewing the published full user studies based on ACM Digital Library and IEEE Xplore databases, they analysed independent variables (IVs), dependent variables (DVs) and the relationship between the IVs and DVs. They found that there is little consensus, and most user studies are lab-based studies. They also found that many studies adopted and focused on usability measurements, and usability is well-represented in both IV categories and DV categories. In view of their findings, they concluded that there is a solid foundation of usability research, and voice-based systems appear to satisfy basic usability criteria.

Taken together, a growing body of literature has investigated chatbot usability, including investigations on a specific types of chatbots [17]–[19], a qualitative study of critical factors that affect users' perception of chatbots [20], a discussion on chatbot quality attributes [21], and a quantitative user experience research on voice-based chatbots [22]. To the best of our knowledge, however, there is no work specifically investigating chatbot usability experimentation. Therefore, our research should fill this gap.

B. FAMILY OF EXPERIMENTS

As mentioned above, ESE plays a role in chatbot usability evaluation, and the experimental process could be used as a checklist and guideline. Once the experiment has been conceived, the general steps of the experimental process are: scoping, planning, operation, analysis and interpretation, presentation, and packaging, after which the chatbot usability experimental report can be drafted [23]. These steps were adopted in [9], for example, to evaluate a chatbot named SOCIO. SOCIO is a collaborative modeling tool to construct models or meta-models through social networks. This study employed a two-sequence, two-period withinsubjects crossover design. The usability of chatbot SOCIO was determined by the attributes of efficiency, effectiveness, satisfaction, and the quality of the results. By comparison with Creately, a tool serving a similar purpose, the statistical results showed that chatbot SOCIO performance was superior in terms of efficiency and satisfaction and some aspects of diagram quality.

Nevertheless, the scientific community unanimously agrees that, with few exceptions, single experiments are of limited value. The accuracy of the baseline experiment results can only be established by replicating and contrasting results [24]. A family of experiments is a set of experimental replications where the experimental design and protocol is known. A family of experiments provides access to the data (raw or aggregated) for each experiment and contains at least three experiments with at least two different technologies testing the same response variable [25]. Families of experiments provide greater statistical power due to the higher number of experimental subjects [26].

More and more families of experiments are being run in SE [25]. As Basili *et al.* [27] stated in 1999, *''families of experiments refer to a group of experiments that pursue the same goal and build a body of knowledge by combining and generalizing the result''*.

Families of experiments are necessary to investigate the effects of alternative values for important attributes of the experimental models, vary the strategy with which detailed hypotheses are investigated, and make up for certain threats to validity that often arise in realistically designed experiments [26]. However, they are not infallible. SE families of experiments share common limitations: they tend to be comprised of fewer studies than those usually gathered in systematic literature reviews (SLRs) and usually study fewer response variables than SLRs, etc. [25].

In particular, families of experiments provide software engineering researchers with some advantages for evaluating the effectiveness of SE tools [28]–[32]: (i) families of experiments provide access to raw data so that researchers can apply consistent measurements and analysis techniques to analyze the experiments, and, hence, increase the statistical power of the findings; (ii) researchers conducting families of experiments may opt to reduce the number of changes made throughout the experiments, which can increase the internal validity of joint conclusions, and (iii) families increase the reliability of the findings, since joint conclusions are not affected by already published results. Due to the strengths of families of experiments, we pay special attention to the adoption of families of experiments in chatbot usability evaluation.

III. RESEARCH METHOD

The secondary study reported in this paper has been developed following the guidelines established by Kitchenham *et al.* [33] and Petersen *et al.* [34] to perform a literature review using a SMS in the fields of SE and HCI. To conduct the research, the first SMS phase is dedicated to identifying the need and corresponding databases for the review, including goals and research questions, and also the search strategy as detailed below.

A. OBJECTIVES AND RESEARCH QUESTIONS

A SMS in SE is a type of secondary study designed to give an overview of a research area by classifying and categorizing published research reports and results and providing a visual summary or map [34]. Since the field of our study is relatively unexplored, a SMS is a good option for this study [23].

The main objective of this study was to map the chatbot usability experiments with respect to aspects of publication status, investigated research questions and metrics measured in the experiments. This gave rise to the following research questions (RQ):

RQ1: What is the state of the art of chatbot usability experimentation?

RQ2: What research questions did chatbot usability experiments investigate?

However, experimental research in SE has not yet been standardized [35]. In view of this, we propose a third research question, namely:

RQ3: How do experiments evaluate chatbot usability?

B. SEARCH STRING SELECTION

We identified the search string keywords as part of a previous study [11]. We ran a pilot study testing different combinations of keywords and analyzing the results for the different databases used. This study was defined in [11]. Finally, we selected the search string (see Table 1) that optimized both the quantity of hits and the share of each database in the process.

C. DATABASES AND SEARCH PROTOCOL

The IEEE Xplore, ACM Digital Library, SpringerLink, Scopus, and ScienceDirect academic databases (DBs) were used in the SMS process. Following the advice of Kitchenham *et al.* [33], we used more than one database to prevent any possible database-derived bias [36]. The search fields used were determined by the options provided by each DB. Table 2 summarizes the search fields used for each DB.

TABLE 2. Search fields by databases.

The selection criteria used to retrieve the primary studies are summarized below.

Inclusion criteria:

- The abstract or title mentions an issue regarding chatbots and usability **OR**
- The abstract mentions an issue related to usability engineering or HCI techniques **OR**
- The abstract mentions an issue related to user experience **AND**
- The paper describes a chatbot usability experiment.

Exclusion criteria:

- The paper does not report an evaluation or an experiment related to chatbot usability **OR**
- The paper does not report any issue related to chatbots and usability **OR**
- The paper does not report any issue related to chatbots and user interaction **OR**
- The paper does not report any issue related to chatbots and user experience **OR**
- The paper is written in a language other than English.

D. SEARCH PROCESS

We reviewed papers about experiments describing chatbot usability published from January 2014 to June 2021. The search was conducted in three phases. The first search phase was run in October 2018, including papers published from January 2014 to October 2018. The second search phase was run in June 2020 and contained papers published from November 2018 to June 2020. The third search phase was run in June 2021 and contained papers published from

July 2020 to June 2021. Since most databases were not searchable based on post month, we searched based on post year (e.g., 2018 to 2020) during the second and third phases and then eliminated duplicate results with previous SMS. Additionally, we searched for publications in the tables of contents of the proceedings of HCI conferences and HCI journals from 2014 to 2021. We have uploaded the lists of HCI conferences and HCI journals that we searched to supplementary material (shorturl.at/dxMR5).

Once we had identified the search strings and defined the search fields (Table 2), we started our search process. A total of 718 papers (referred to as retrieved papers) were found in the different DBs, HCI conferences, HCI journals or were recommended by external HCI experts. In particular, external HCI experts recommended 5 journal articles, 10 conference papers and 8 papers, which account for the 23 papers from other sources.

Then, the duplicate papers were removed from the retrieved papers, 560 papers were filtered to the group of nonduplicate retrieved papers. A peer review was carried out on these 560 papers applying the inclusion and exclusion criteria to the title and abstract. Discrepancies were resolved through discussion. As a result, we identified 113 candidate papers.

To determine if the candidate papers were relevant to chatbot usability and the execution of chatbot usability experiments, we reviewed each candidate paper again using the inclusion and exclusion criteria. However, this time we read the papers in full (i.e., a full-text review). The results were cross-checked by two experts from the HCI and ESE fields.

Finally, a total of 28 were selected as the experiment papers used in this study. Of the experiment papers, seven were sourced from outside the database: two were retrieved from HCI conference, and five were recommended by external HCI experts (our search did not identify these papers due to the defined search strings). These papers were included as other sources in Figure 1 and Table 3. During the search process, we were not able to review one of the candidate papers. As it was not downloadable, it was discarded from this analysis. The results of the selection were assessed by two of the authors who are experts in HCI and ESE, and any disagreement was discussed and resolved. The steps for conducting the review are shown in Fig. 1. Table 3 reports the number of papers taken from each group: most experiment papers were taken from the Scopus database. The 28 experiment papers used in the analysis and extraction of the results are shown in Appendix A.

With the aim of solving disagreements between researchers in the primary study selection process, we evaluated inter-rater reliability by applying two assessments [37]: (i) percentage agreement [38], and (ii) Cohen's Kappa coefficient (k) [39]. For the first assessment, the observed percentage agreement was 87%, indicated by the total number of papers on which both researchers reached an agreement (488 papers), divided by the total number of reviewed papers (560 papers) (see Table 4). This is considered acceptable.

FIGURE 1. Diagram of the steps for the selection of experiment papers.

TABLE 3. Number of studies remaining after filtering the database results.

DBs	Retrieved	Non- Duplicate Retrieved	Candidates	Exper- iments
IEEE Xplore	132	90	15	2
ACM Digital Library	52	49	13	5
SpringerLink	176	148	14	$\overline{2}$
Scopus	279	217	59	11
ScienceDirect	56	40	2	
Other	23	16	10	
Total	718	560	113	28

TABLE 4. Agreement matrix for nominal variable.

For the second assessment, $k = 0.66$. According to [40], this is indicative of substantial agreement.

IV. RESULTS

This section reports the results of the SMS and responses to the research questions.

RQ1: What is the state of the art of chatbot usability experimentation?

To answer this research question, we analyzed 28 papers. They are mostly quantitative, and they performed controlled experiments by comparing chatbots with extended

FIGURE 2. Mapping showing the experiment papers according to usability characteristics, including publication type and year.

versions of chatbots or other software with similar functions. Fig. 2 presents an overview of the identified primary studies.

As shown in Fig. 2, the results have been segmented into two areas. The left-hand side consists of two scatter (XY) plots (top and bottom) with bubbles at the junctions of the year-type of publication categories (top left-hand side) and usability characteristic-type of publication categories (bottom left-hand side). The types of publications were conferences, journals, and book chapters. The size of each bubble was determined by the number of experiment papers that had been classified into each category. The right-hand side of Fig. 2 illustrates the number of primary studies published per year. As the top right-hand side of Fig. 2 shows, the interest in chatbot usability experimentation is increasing and is very recent, with the earliest papers dating from 2018. Considering that the search end date was June 2021, the number of papers identified by our SMS for 2021 is rather high. Satisfaction is the most widely used usability characteristic (bottom lefthand side) as it was measured in each and every experiment. Note that the number of papers at the bottom of Fig. 2 does not match the number of papers at the top. The reason is that the same paper can discuss several usability characteristics.

Table 5 indicates the publication source of selected papers and type of publication $(J =$ journal, $C =$ conference, $B =$ book chapter). In terms of the type of publication, 46.4% (13) of publications are conference papers, 35.7% (10) are journal articles, and 17.9% (5) are book chapters.

RQ2: What research questions did chatbot usability experiments investigate?

Table 6 summarizes the research objectives of the selected papers, including information like the references, the goals

TABLE 5. Publication source.

of the experiment, the stated or modified research questions and hypotheses of the experiment, the respective responses, whether the experimental raw data were provided and chatbot types.

Note that some papers defined the research question implicitly or stated multiple research questions. In the first case, we opted for the research question addressed by the

TABLE 6. Summary of research questions.

usability experiment based on their experiments (identified in Table 6 with an asterisk). In the second case, we selected the research questions related only to usability.

The raw data (fifth column, Table 6) were poorly reported. We found that only one paper provided access to experiment raw data and three provided some of the experiment raw data as textual records. The chatbot types are listed in the sixth column of Table 6. We found that many chatbots are used in a number of real-life scenarios: 67.9% of the chatbots reported in our primary studies are deployed as personal assistants

on most aspects against the Creately baseline.

if in the process research model, if supported, would reveal flow factors, such as perceived autonomy, co
jointly influence user satisfaction with the interaction process, task performance, and ultimately the systems itsel ψ

comparing the results for the baseline group (use chatbot only) and control group (read a self-help guidebook only), they specifically evaluated the metrics of the measurement effectiveness and satisfaction. The results show that the chatbot Todaki was effective enough to reduce the overall symptoms related to attention deficits, albeit with less subjective satisfaction of the users.

[PS2], [PS4], [PS5], [PS6], [PS7], [PS10], [PS11], [PS13], [PS14], [PS16], [PS17], [PS18], [PS20], [PS21], [PS22], [PS23], [PS24], [PS26], [PS28] and more and more chatbots are being deployed in the healthcare domain [PS5], [PS7], [PS14], [PS21], [PS23], [PS25].

Chatbots have the potential to be at the patients' side anytime and anywhere, which is, obviously, out of the question for doctors and care workers, leading researchers to develop chatbots to support healthcare. Even though the demand for measuring the performance of healthcare chatbots is increasing, the evaluation methods for healthcare chatbots appear to be wide-ranging and arbitrary [17].

Additionally, some chatbots act as e-commerce tools [PS9], [PS12], [PS27], collaborative tools [PS8], emotionally aware conversational agents [PS1], astrophysics assistants [PS15], tourist guides [PS11], [PS20] and recommenders [PS3], [PS19].

RQ3: How do experiments evaluate chatbot usability?

From the perspective of HCI, various usability techniques were employed in these experiments, and it is patent that the most employed usability technique was questionnaires, followed by interviews (Table 7).

Compared with [11], we found that, on top of SUS and adhoc methods, a broader range of questionnaires were adopted to investigate chatbot usability. In [PS2], the AttrakDiff2 questionnaire was used, which measures how attractive a product is based on its hedonic and pragmatic qualities. The Likert scale was the most used metric in the questionnaires across the whole range of papers [PS3], [PS6], [PS9], [PS12], [PS21] and [PS23].

TABLE 7. Usability techniques.

Throughout the usability evaluation process, pre-test and post-test questionnaires were combined for use in [PS5] and [PS10] in order to round out the result of evaluation with demographic information. We also noticed that papers seldom discuss the rationale used to select the technique. It should be noted that the selected technique may have an impact on the effectiveness and reliability of the experimental result.

The columns of Table 8 show the metrics used to evaluate the experiment results, specifying whether the results correspond to a family of experiments $(F = "Is the experimenta$ tion composed of a family of experiments?''), the number of experiments $(ES = experiment size)$, the experiment sample size $(SS = sample size)$, the types of subjects participating in the experiments $(TS = type of subjects)$, experimental design and procedure, the implemented tasks of the experiment, usability characteristics used to measure the results, measurement instruments (MI), and statistical technique (ST).

Our topic cuts across the fields of HCI and ESE. Therefore, we considered the indicators to measure the experiment

from both sides, as the software development process is very dependent on the defined tasks and user skills and characteristics [13], and the task and users matter to the HCI community.

We also observed a growing interest in experimentation and have taken note of recent calls for replication in SE [24]. Thus, we considered investigating replication in chatbot usability experimentation. We mainly followed the reporting structure for SE experiment reports proposed by Jedlitschka and Pfahl [41]. As the defined tasks and user skills and characteristics have a profound impact on the software development process [13], the task and users matter in HCI. For the above related reasons, we decided to use the indicators shown in Table 8 to measure each experiment.

We noticed that chatbot developers always acted as evaluators in these experiments. Only six experiments were conducted by third-party researchers or experts who evaluated the usability of the chatbots [PS8], [PS13], [PS17], [PS18], [PS26], [PS28].

A. THE REPLICATION OF EXPERIMENTS

Of the usability experiments that we reviewed, there is only one study [PS6] that conducted replications of an experiment with a consistent experimental design but different participant region or background. We consider the study reported by Huff-Jr *et al.* as a family of experiments, which uses a withinsubjects mixed-method design [PS6] using qualitative contents and a multilevel linear model to analyze data. The total sample size of the replication was 35, although the authors did not report the respective sample size of each replication.

To the best of our knowledge, a family of experiments should include at least three experiments [25], whereas [PS6] replicates a single experiment—that is, this paper reports a set of two experiments. However, since two experiments can aggregate the data to evaluate the effect of chatbots, we classified the two experiments as a family of experiments.

It should be noted that there is a study [PS22] that conducted two different experiments in controlled laboratorybased and real-world environments to comprehensively evaluate the usability of their chatbot. Since the experimental designs are different, we do not consider this study to be a family of experiments.

B. SAMPLE SIZES

Regarding the sample size of experiments (fourth column of Table 8), although we acknowledge that the sample size varies for different usage and developmental phases, the sample sizes of published usability experiments for chatbots are relatively small. Of the experiments, 42.9% (12) included fewer than 30 subjects, 42.9% (12) included between 30 subjects and 80 subjects, and 10.7% (3) contained more than 90 but fewer than 500 subjects. One experiment [PS11] did not detail the sample size.

C. TYPES OF SUBJECTS

In terms of the types of subjects involved in experiments (fifth column of Table 8), 35.7% (10) of the experiments

included students, while most of the researchers placed no constraint on academic background and academic program. The remaining experiments included experienced users or experts, company employees, farmers, children, residents, and patients. However, 25% (7) of experiments did not define the subject types. Only two studies compared groups: graduates versus undergraduates [PS8] and native vs. non-native English-speakers [PS26].

D. EXPERIMENTAL DESIGN AND PROCEDURE

Regarding the experimental design and procedure, 53.6% (15) were defined as within-subjects experiments. As the sample sizes of the identified experiments are relatively small, the within-subjects design has better statistical power since it doubles the data points. In SE, experimental design plays a role in controlling for extraneous variables: mature experiments are run with pre-established protocols defining the experimental settings and the set of procedures that must be strictly adhered to during the execution and analysis of the experiments. By contrast, many chatbot usability experiments are set up without any a priori plan or experimental design definition.

Furthermore, prior experience and technical knowledge have an impact on the global usability of conversational agents [PS13], [PS26], while some experiments [PS1] did not appear to measure the pre-user experience or knowledge related to chatbots.

Generally, chatbot usability was rated positively in most experiments, while only one chatbot was given a negative evaluation compared with the control tool [PS6]. Despite this, it was pointed out that chatbots still need to be improved in some respects. The NL interaction was the most frequently mentioned improvement within these experimental results.

The result for [PS3] shows that the performance of NL interaction with the chatbot CoRS is poorer than the button and mixed interfaces. In [PS8], several participants suggested an improvement in natural language processing (NLP) as the chatbot SOCIO does not understand some phrases. Aside from these, researchers also suggested voice-based natural language recognition should be improved to support varieties of English accents [PS26].

Besides, chatbot personalization does not always satisfy all users and experts. In [PS1], the users commented that the automatic adaptation strategies need to be further improved to reach the level of personalization desired by the users compared to manual adaptation.

There are some other problems that remain. In [PS8], the control outperforms the chatbot SOCIO in terms of recall and perceived success. A Shakespearean-styled chatbot increased user engagement as well as perceived product value, but user satisfaction decreased [PS9]. As for chatbot use for online shopping, the researchers found that the participants' expressed re-use intentions and the level of recommendation to others were not as high as expected [PS24].

TABLE 8. (Continued.) All measured metrics of experiments. **TABLE 8.** (Continued.) All measured metrics of experiments.

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E. TASKS

Regarding the implemented experimental tasks, 35.7% (10) of the experiments contained between two and six tasks, 42.9% (12) contained only one task, three experiments required participants to perform 10 tasks, 12 tasks and 13 tasks respectively [PS26], [PS28], [PS2], and two experiments did not specify the number of tasks [PS13], [PS15].

F. USABILITY CHARACTERISTICS

In terms of usability characteristics used to measure the results, the surveyed experiments measured usability based on effectiveness, efficiency, and satisfaction. Of the experiments, 32.1% explored all three aspects [PS2], [PS3], [PS5], [PS8], [PS12], [PS17], [PS18], [PS19], [PS25], 32.1% explored efficiency and satisfaction [PS4], [PS7], [PS9], [PS10], [PS11], [PS15], [PS16], [PS21], [PS24], 25% explored only satisfaction [PS1], [PS6], [PS14], [PS22], [PS23], [PS26], [PS27], and three studies explored effectiveness and satisfaction [PS13], [PS20], [PS28].

We follow the definition of satisfaction given in ISO/IEC 25010 [16]: *''The degree to which users' needs are satisfied when a product or system is used in a specified context of use.''* Satisfaction is the usability characteristic of most concern to researchers since it was evaluated most often. The measures of satisfaction primarily include ease-of-use, contextdependent questions (or inconsistency), satisfaction before and during use, complexity control, the physical discomfort of the interface, pleasure, the willingness to use the chatbot again (or intent to use the chatbot again), and enjoyment and learnability. Of the measures of satisfaction, ease of use, pleasure, and willingness to use the chatbot again were the most frequently measured, as shown in Table 9.

We found that in recent years more chatbot designers are inclined to evaluate the usability of the chatbot in order to put it into use in real life or in industry rather than for research or scholarly purposes. In [PS3], chatbot developers wanted to know if participants have a willingness to pay or know the price they are willing to pay. In [PS3], [PS9] and [PS12], they investigated whether participants intend to use their chatbot in real life.

It is obvious that more chatbots can afford more complex functions: the chatbot in [PS3] is equipped with a sentiment analyzer as it discovers items that best fit users' needs. Effectiveness is defined as the accuracy and completeness with which users achieve specified goals in the HCI field [16], [42]. From Table 10, we find that task completion and error rate are the effectiveness measures of most concern.

Efficiency is defined as the resources expended in relation to the accuracy and completeness with which the users achieve their goals in the HCI field [16], [42]. From Table 11, we find that more research focuses on measuring task completion time.

In [PS3], they measure detailed time spent per question and the number of concepts the user can introduce for each message from the chatbot. We discovered that the hedonic

TABLE 9. Measures of satisfaction.

TABLE 10. Measures of effectiveness.

TABLE 11. Measures of efficiency.

quality of conversation is relevant to the chatbot's efficiency since the effort required for users to understand and answer a chatbot request is frequently measured. In conclusion, it is clear that researchers have sought to understand chatbot reaction time and clarity of speech.

G. MEASUREMENT INSTRUMENTS

Measurement instruments refer to the instrument used to measure the experiment result quantitatively. Of the

TABLE 12. Descriptive statistics representation.

experiments, 92.9% (26) adopted questionnaires to measure chatbot usability, and almost all the usability questionnaires have undergone some type of psychometric evaluation [43], 57.1% (16) adopted software platforms to record participants' interaction or input information objectively, 21.4% (6) adopted interviews to record participants' answers to openended questions, and three experiments used video recording. Of the measurement instruments, questionnaires and software platforms were most frequently combined. We also observed that one experiment used the questionnaire without recording quantitative data. It is important to note that usability is not a one-dimensional software property: usability is a concept that includes effectiveness, efficiency, and satisfaction.

Usability techniques are different from measurement instruments. Measurement instruments are methods to measure and collect experimental data, whereas usability techniques refer to HCI techniques used in the usability evaluation process to raise the usability level of the software product. They could be methods of inspection, inquiry, or testing.

H. STATISTICAL TECHNIQUES

The statistical techniques used in the experiments are categorized from four perspectives: descriptive statistics, inferential statistics, a general linear model (GLM), and qualitative research. Descriptive statistics (Table 12) are representation methods that visually integrate multiple datasets to contextualize the data and improve reader understanding.

Of the 28 experimental results on chatbot usability, descriptive statistics tables and textual description were the most used presentation formats. Descriptive statistics tables and frequency distribution tables were used to understand the collected data in numerical form. Textual description always reports the effect size and confidence interval. Box plots were used to report the sample dispersion and skewness [23] (e.g., task completion rates of two compared tools [PS2]). There is one experiment that has not yet been executed [PS11].

Inferential statistics (Table 13) were used to analyze 18 experiment results. Inferential statistics deals with the process of using data analysis to deduce properties of an underlying probability distribution [44]. Inferential statistics methods are classified into parametric statistics and nonparametric statistics.

TABLE 13. Inferential statistics methods.

In general, parametric statistical tests, like Pearson correlation, paired *t*-test, and *z*-test, assume that some of the parameters are normally distributed. The Pearson correlation analysis is conducted in order to describe how a measurement of A is related to a measurement of B [23]. As the result of the analysis, the researchers in [PS2] claim that there was a partial correlation between the results of the physiological measurements and the UX quality evaluation results. In most cases, the *z*-test is an inference on a population of known variance, while the *t*-test is adopted if variance is not known. Nonparametric tests, such as the Wilcoxon and Mann−Whitney tests, were used in six experiments when experiments have one factor and two treatments. Note that the authors of [PS13] and [PS3] did not specify which of the *t*-tests and Wilcoxon tests they used, respectively.

I. LINEAR MODELS

The GLM category of methods are parametric tests used to describe the concept of the model. A GLM ensures that the estimated values provide the best possible linear fit to the data, minimizing the error with the least square method [45]. The analytical methods are ANOVA and regression, which are variations of GLM [46]. In terms of regression, 5 studies in Table 14 used linear regression (e.g., the Durbin–Watson test), and logistic regression and mixed effect models were

each used once. ANOVA and MANOVA were also used in 7 experiments. In [PS3], they conducted a MANOVA statistical test on all the accuracy and cost of interaction metrics of usability experiments, whereas two-way ANOVAs were used to investigate the interaction effect between prior experience and technical knowledge on overall chatbot usability in [PS13].

TABLE 14. General linear model.

Qualitative research (Table 15) was conducted in 39.3% of experiments. The researchers analyzed the contents, specifically recording interviews and answers to open-ended questions, whereas [PS16], [PS23] and [PS27] adopted thematic analysis to analyze recorded interviews and user utterance data, respectively.

TABLE 15. Qualitative research.

Additionally, most researchers did not explain the motivation behind technique adoption or indicate the challenges or advantages of adopting the technique. Some analysis decisions within chatbot usability experiments were affected or driven by previous examples from other researchers and personal preferences [PS2].

V. DISCUSSION

The mind map in Fig. 3 shows a summary of the five main aspects associated with chatbot usability experimentation, which are identified in the literature of our SMS: (i) measures, (ii) types of chatbots, (iii) usability techniques, (iv) descriptive statistics representation, and (v) inferential statistics methods.

The center of Fig. 3 corresponds to our research topic (Level 0 of the mind map). Five branches that point away from the center of the mind map symbolize the five abovementioned aspects (Level 1). Another three hierarchical values—*effectiveness*, *efficiency*, and *satisfaction—* (Level 2) associated with the measured values branch off. At Level 3 of the mind map, values correspond to each item of the immediately preceding branch.

Continuing with our example, the measured values of *effectiveness* are *accuracy*, *expert* and *user assessment*, *number of errors/error rate*, *precision*, and *task completion*. Finally, at Level 4 of the mind map, experiment papers report the characteristics of the previous branch. Continuing with our example, the experiment reported in paper [PS3] corresponds to *accuracy*.

When conducting an SMS, the search strings should provide a broad overview of the research area [34]. Considering that chatbot usability experimentation is a relatively small field, we chose search strings that consisted of two components —synonyms of the terms ''chatbot'' and ''usability'' that helped to identify as many relevant papers as possible. We experimented with more than one synonym of the terms that formed different search strings to choose the best search string. Although our goal is to conduct an analysis of chatbot usability experimentation, we noticed that the interfaces of most current chatbots take the form of a NL dialog: the development of chatbots has become standardized because many platforms built for different goals and usages (e.g., Google's NLP platform and Dialogflow) have been widely used [PS1], [PS6], [PS10].

Of the initial 718 papers selected from well-known electronic research databases, 28 studies were selected following a rigorous screening process during which disagreements found during the selection process were resolved. The comparison of two or more treatments and the randomization of the subjects were key points for identifying whether the study described an experiment [23] when we reviewed each paper.

Regarding theoretical models, a few of the 28 experiments discussed theories that inspired research questions. In paper [PS11], we learned that self-determination theory was used to propose a research model to study the factors that affect chatbot satisfaction. On the other hand, most usability questionnaires assessed usability at the end of a study [43]. Selfdesigned questions [PS12], [PS14], [PS15], [PS18], [PS24] and standardized questionnaires are the two main usability scales used. However, the adoption of usability scales varies a lot in chatbot usability experiments, because it mainly depends on the research goal and chatbot type.

Researchers developed multiple questions for selfdesigned questionnaires according to their research topics and measurements. For example, researchers developed, based on the SUS questionnaire, the Voice Usability Scale for speech-based systems, as SUS does not comprehensively account for several characteristics that are unique to a voice environment [PS18]. Most experiments used standardized usability scales (like Affective Slider [PS1], ResQue model [PS3], [PS19], SUS [PS6], [PS8], [PS14], [PS17], SUMI [PS13], Adjective Rating Scale [PS18], Usefulness, Satisfaction, and Ease of use questions [PS23], User Engagement Scale [PS25]), whereas scales cited in national and international standards (SUS and SUMI) were adopted in only five experiments.

The chatbot usability experiment correlates to chatbot development. In general, evaluations of chatbot usability were considered as a part of the software development process. However, there are two experiments related to a usability experiment on an advanced or modified version of a chatbot [PS12], [PS15].

FIGURE 3. Main aspects of the research on chatbot usability experimentation.

For experimental results to be reliable, all the treatment aspects (except for factor manipulation) should be similar across all groups, as irrelevant variables pose a threat to validity.

We found that many studies did not clearly state extraneous variable control in their experimental designs. For example, they did not discuss the possible learning effects between different sessions [PS6], [PS10], if there was a short break between the different experiment sessions to avoid participant fatigue [PS1], [PS3], or whether the experimental environments were consistent in different sessions [PS4], [PS5].

We observed that most chatbot experiments were based on some specificities—including relatively small sample sizes, subjects coming from a specific background, preset tasks, and whether it was the users' first contact with a chatbot as the expansion of the experimental results to an industrial setting was very limited. Besides, there was research that had not published the experimental results as of our search date. The proposed experimental setting in [PS11] included the procedure, type of subject, measurements, and analysis methods, but the sample size and experiment result were not provided.

VI. THREATS TO VALIDITY

The first threat to validity of this research is the bias in the paper selection process. Although the selection criteria and results have been double-checked and accepted by other authors, the publications were evaluated and classified based on our criteria and experience, and other researchers may have evaluated the publications differently. To improve the inter-rater reality, we provide percentage agreement and Cohen's Kappa statistics to evaluate disagreement between researchers (see Section 3).

The second point is related to the type of studies included in this investigation. We expanded the search scope by using search strings that identified a wider range of publications: the paper retrieval steps were as shown in Fig. 1 and the selected papers were grouped according to different dimensions as shown in Table 8. On the one hand, this systematic study was developed using five popular databases (IEEE Xplore, ACM Digital Library, SpringerLink, Scopus and ScienceDirect), as they are regarded as the most complete and most used databases in SE. On the other hand, this search only includes papers written in English. Nonetheless, the final number of studies focusing on exploring chatbot usability is relatively small—relevant papers produced by additional databases or resources or written in other languages or using other synonyms of chatbot could have been overlooked.

VII. CONCLUSION AND FUTURE WORK

This section reports the final conclusions of the study based on the research questions stated above.

RQ1: What is the state of the art of chatbot usability experimentation?

Chatbot development usability testing is not a new concept, but chatbot usability experimentation has emerged recently.

Our SMS found that researchers started to evaluate the usability of chatbots through experimentation in 2018 (Fig. 2).

Several usability techniques have been used to collect usability data: questionnaires, interviews, think-aloud and direct observation. Of these techniques, questionnaires (applying various scales and types) are the most used technique. With regard to publication venue, half of the reviewed papers in our SMS were published at conferences.

In summary, chatbot usability experimentation tends to have the following characteristics: (i) very few raw data were provided (see Table 6); (ii) there was a range of chatbot types due to their usage scenarios, where a total of 67.9% of the experiments investigated chatbots pertaining to personal assistants, especially in the healthcare domain (Table 6); (iii) most experiments did not clearly define the research questions, hypotheses, or provide original data (Table 6), that is, they did not apply ESE methods to set up the experimental design [23], which may lead to weak experiment replicability; (iv) satisfaction, efficiency, and effectiveness were the main evaluated chatbot usability measures in most experiments (Tables 9, 10 and 11), and (v) parametric tests were the inferential statistics commonly used to analyze the experimental results in most studies (see Table 13).

RQ2: What research questions did chatbot usability experiments investigate?

Table 6 lists all the research questions used in the selected studies from five perspectives: (i) the goals of the experiment, (ii) the stated, selected or supplemented research questions, (iii) experiment hypotheses, (iv) answers to respective research questions and hypotheses, (v) provision of the experimental raw data, and (vi) chatbot types.

Regarding the treatment applied in these experiments, we found that control tools are commonly applied in experiments, and relatively few studies used the web or a reallife product [PS1], [PS2], [PS5], [PS8], [PS17], [PS18], [PS26], [PS28]. To determine whether the chatbot was able to provide a similar experience to the user, some developed different versions of chatbots with different functions or expression [PS3], [PS9], [PS10] to identify user preferences and how to operate differently depending on different user populations.

In general, most studies investigate not only usability factors but also the quality of the interaction or chatbot performance [PS3], [PS7], [PS8], [PS10], [PS28] in order to understand chatbot usability comprehensively. Also, some studies investigated the relationships between usability and other factors (e.g., acceptability, interface workload, and similarity) [PS5], [PS10], [PS14].

Most experiments did not provide access to raw data. The raw data may be withheld from the public domain either because they are confidential or because the researchers want to continue publishing data analyses sometime in the future [25]. However, this situation prevents rigorous peer review and stops third-party researchers from reanalyzing data using aggregation techniques that may be better suited than the original method [25].

FIGURE 4. Research gaps and future direction.

RQ3: How do experiments evaluate chatbot usability?

As for chatbot usability experiments, we analyzed the evaluation metrics from nine perspectives, shown in Table 8: (i) whether the experiment is part of a family of experiments; (ii) the number of experiments; (iii) the experiment sample size; (iv) the types of subjects participating in the family; (v) experimental design and procedure; (vi) the implemented experimental tasks; (vii) usability characteristics used to measure the results; (viii) measurement instruments; and (ix) statistical techniques.

After reviewing the chatbot usability evaluations, we found that: (i) the families of experiments have seldom been used in this field so far since we found only one experiment replication; (ii) within-subjects experiments are generally the most popular design in chatbot usability experimentation; (iii) a total of 42.9 per cent of the experiments included a small sample size (under 30 subjects) and subjects are mostly students, and (iv) the number of tasks is relatively small, as most of the experiments applied fewer than six tasks.

The evaluation results revealed some common problems that existed within these chatbots. NL interaction (or natural mode of interaction) was the most cited problem. In general, chatbots satisfied and surprised users in basic interactions by using NL. However, chatbots required more effort from users in complex or flexible interaction and cannot yet compete with to human−human interaction. Chatbot personalization

was the second issue mentioned, especially with respect to chatbots designed to target people with special needs, like students who require special mentorship or children with a specific disease. These chatbots should be highly adjustable, efficient, attractive in appearance and even have a physical embodiment. The experimental results show that personalization still needs improvement.

In terms of usability characteristics, satisfaction is of more concern than efficiency and effectiveness. The overall user experience, ease of use, and pleasure are the most frequent metrics used to measure satisfaction. Various studies assessed different aspects of satisfaction, complicating direct comparison. Some of this variation (e.g., adaptability [PS3], helpfulness [PS15], context-dependent question [PS4], and hedonic quality [PS2]) may be due to the individual characteristics of chatbot implementations and their distinct use cases [47]. On the other hand, task completion and number of errors/error rate are the effectiveness characteristics of most concern and have been measured a total of 9 times. With regard to efficiency, task completion time was measured most frequently.

Questionnaires and software platforms were the most popular measurement instruments. Questionnaires were commonly used for opinion polls [23], and software platforms were employed to record information for statistical analysis. Then, the collected information could be arranged in a quantitative or qualitative manner [23], and most researchers

counted measurable values or analyzed the contents (e.g., the record of the interview, the answers to the open-ended questions), or ran parametric (e.g., *t*-tests) or nonparametric (e.g., Wilcoxon, Mann−Whitney tests) statistical tests depending on the experimental design type.

The research gaps shown in Figure 4 are used to identify experimental features associated with chatbot usability. They include defining each response variable clearly during the process of experimental design. In order to clearly report the execution of a chatbot usability experiment, factors like blocked variables, number of experimental sessions, factors per session, and the number of treatments in each session need to be properly specified in the design of the experimental execution. The clarification of responsibilities and division of labor for experimenters also helps in understanding the experimental process. Further, we encourage the measurement of usability characteristics whenever possible in order to gain a comprehensive understanding of chatbot usability. With regard to the data analysis and aggregation process, not enough raw data are provided, and families of experiments or experiment replications have seldom been reported to date. In view of this, we encourage future researchers to: (i) provide access to full raw data to guarantee the replicability of the experiment and the transparency of results to promote a better measurement of usability characteristics and a greater understanding of chatbot usability; (ii) clearly indicate the required characterization of chatbot usability experiments by including effect sizes, operationalization, design of the experimental execution, the experimenters; (iii) consider families of experiments or the possibility of conducting replications of the baseline experiment to consolidate the experimental results and increase the statistical power, and (iv) measure as many usability characteristics as possible to provide a thorough understanding of chatbot usability.

Future research may use and include the results of this SMS, especially the characteristics of chatbot usability experiments identified in this investigation, as a basis for conducting more studies to investigate this topic. Considering that the research is limited by search date, databases, and search strings, this study could be replicated in a future study. This is certainly an open research problem that requires further investigation. Based on the result of this research, we plan to conduct a family of experiments to evaluate the usability of a chatbot with an advanced version to fill the gaps and explore the topic further.

APPENDIX A PRIMARY STUDIES

This appendix lists the references of the primary studies used for the mapping study described in this paper.

[PS1] S. Katayama, A. Mathur, M. Van den Broeck, T. Okoshi, J. Nakazawa, and F. Kawsar, ''Situation-aware emotion regulation of conversational agents with kinetic earables,'' in *Proc. 2019 8th International Conference on Affective Computing and Intelligent Interaction (ACII'19)*, Cambridge, UK, 2019, pp. 725−731.

[PS2] S. Lee, H. Ryu, B. Park, and M. H. Yun, ''Using physiological recordings for studying user experience: Case of conversational agent-equipped TV,'' *International Journal of Human Computer Interaction*, vol. 36, no. 9, pp. 815−827, Feb. 2020.

[PS3] F. Narducci, P. Basile, M. de Gemmis, P. Lops, and G. Semeraro, ''An investigation on the user interaction modes of conversational recommender systems for the music domain,'' *User Modeling and User-Adapted Interaction*, vol. 30, pp. 251−284, Mar. 2020.

[PS4] J. Guo, D. Tao, and C. Yang, ''The effects of continuous conversation and task complexity on usability of an AI-based conversational agent in smart home environments,'' in: S. Long, B. Dhillon (Eds.), *Man–Machine–Environment System Engineering,* MMESE'19, (pp. 695−703). Lecture Notes in Electrical Engineering, vol 576. Springer, Singapore, 2020.

[PS5] A. Ponathil, F. Ozkan, B. Welch, J. Bertrand, and K. C. Madathil, ''Family health history collected by virtual conversational agents: An empirical study to investigate the efficacy of this approach,'' *Journal of Genetic Counseling*, pp. 1−12, Mar. 2020.

[PS6] E. W. Huff-Jr, N. A. Mack, R. Cummings, K. Womack, K. Gosha, and J. E. Gilbert, ''Evaluating the usability of pervasive conversational user interfaces for virtual mentoring,'' in: P. Zaphiris, A. Ioannou (Eds.), *Learning and Collaboration Technologies. Ubiquitous and Virtual Environments for Learning and Collaboration*, HCII'19 (pp. 80−98). Lecture Notes in Computer Science, vol. 11591, Springer, Cham, 2019.

[PS7] R. Håvik, J. D. Wake, E. Flobak, A. Lundervold, and F. Guribye, ''A conversational interface for self-screening for ADHD in adults,'' in: S. Bodrunova *et al.* (Eds.), *Internet Science*, INSCI'19 (pp. 133−144). Lecture Notes in Computer Science, vol. 11551. Springer, Cham, 2019.

[PS8] R. Ren, J. W. Castro, A. Santos, S. Pérez-Soler, S. T. Acuña, and J. de Lara, ''Collaborative modelling: Chatbots or on-line tools? An experimental study,'' in *Proc. Evaluation and Assessment in Software Engineering (EASE'20)*, Trondheim, Norway, 2020, pp. 260−269.

[PS9] E. Elsholz, J. Chamberlain, and U. Kruschwitz, ''Exploring language style in chatbots to increase perceived product value and user engagement,'' in *Proc. 2019 Conference on Human Information Interaction and Retrieval (CHIIR'19)*, Glasgow, Scotland, UK, 2019, pp. 301−305.

[PS10] M. Jain, P. Kumar, I. Bhansali, Q. V. Liao, K. N. Truong, and S. N. Patel, ''FarmChat: A conversational agent to answer farmer queries,'' in *Proc. ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT'18),* vol. 2, no. 4, 2018, pp. 170:1−170:22.

[PS11] Q. N. Nguyen, and A. Sidorova, ''Understanding user interactions with a chatbot: A self-determination theory approach,'' in *Proc. 24th Americas Conference on Information Systems: Digital Disruption (AMCIS'18)*, New Orleans, LA, USA, 2018.

[PS12] M. Jain, R. Kota, P. Kumar, and S. N. Patel, ''Convey: Exploring the use of a context view for chatbots,'' in *Proc. 2018 CHI Conference on Human Factors in Computing Systems (CHI'18)*, Montreal, QC, Canada, 2018, pp. 468:1−468:6.

[PS13] M.-L. Chen, and H.-C. Wang, ''How personal experience and technical knowledge affect using conversational agents,'' in *Proc. 23rd International Conference on Intelligent User Interfaces Companion (IUI'18)*, Tokyo, Japan, 2018, pp. 53:1−53:2.

[PS14] C. Sinoo, S. van der Pal, O. A. B. Henkemans, A. Keizer, B. P. B. Bierman, R. Looije, and M. A. Neerincx, ''Friendship with a robot: Children's perception of similarity between a robot's physical and virtual embodiment that supports diabetes self-management,'' *Patient Education and Counseling*, vol. 101, pp. 1248−1255, Jul. 2018.

[PS15] R. R. Divekar, J. O. Kephart, X. Mou, L. Chen, and H. Su, ''You talkin' to me? A practical attention-ware embodied agent,'' in: D. Lamas, F. Loizides, L. Nacke, H. Petrie, M. Winckler, and P. Zaphiris (Eds), *Human-Computer Interaction*, INTERACT 2019, (pp. 760-780). Lecture Notes in Computer Science, vol 11748. Springer, Cham, 2019.

[PS16] A. Følstad and R. Halvorsrud, ''Communicating service offers in a conversational user interface: An exploratory study of user preferences in chatbot interaction,'' in *Proc. 32nd Australian Conference on Human-Computer Interaction (OzCHI'20)*, Sydney, NSW, Australia, pp. 671–676, 2020.

[PS17] D. S. Zwakman, D. Pal, T. Triyason, and V. Vanijja, ''Usability of voice-based intelligent personal assistants,'' in *Proc. International Conference on Information and Communication Technology Convergence (ICTC'20)*, Jeju, Korea (South), pp. 652–657, 2020.

[PS18] D. S. Zwakman, D. Pal, and C. Arpnikanondt, ''Usability evaluation of artificial intelligence-based voice assistants: The case of Amazon Alexa,'' *SN Computer Science*, vol. 2, article 28, 2021.

[PS19] A. Iovine, F. Narducci, M. De Gemmis, and G. Semeraro, ''Humanoid robots and conversational recommender systems: A preliminary study,'' in *Proc. IEEE Conference on Evolving and Adaptive Intelligent Systems (EAIS'20),* Bari, Italy, pp. 1–7, 2020.

[PS20] D. Potdevin, C. Clavel, and N. Sabouret, ''A virtual tourist counselor expressing intimacy behaviors: A new perspective to create emotion in visitors and offer them a better user experience?,'' *International Journal of Human-Computer Studies*, vol. 150, article 102612, 2021.

[PS21] S. Jang, J. J. Kim, S. J. Kim, J. Hong, S. Kim, and E. Kim, ''Mobile app-based chatbot to deliver cognitive behavioral therapy and psychoeducation for adults with attention deficit: A development and feasibility/usability study,'' *International Journal of Medical Informatics*, vol. 150, article 104440, 2021.

[PS22] T. Bickmore, E. Kimani, A. Shamekhi, P. Murali, D. Parmar, and H. Trinh, ''Virtual agents as supporting media for scientific presentations,'' *Journal on Multimodal User Interfaces*, vol. 15, pp. 131–146, 2021.

[PS23] K. Chung, H. Y. Cho, and J. Y. Park, ''A chatbot for perinatal women's and partners' obstetric and mental health care: Development and usability evaluation study,'' *JMIR Medical Informatics*, vol. 9, no. 3, 2021.

[PS24] Y. Lim, J. Lim, and N. Cho, ''An experimental comparison of the usability of rule-based and natural language processing-based chatbots,'' *Asia Pacific Journal of Information Systems*, vol. 30, no. 4, pp. 832–846, 2020.

[PS25] T. Fergencs, and F. Meier, ''Engagement and usability of conversational search – A study of a medical resource center chatbot,'' in: K. Toeppe, H. Yan, and S.K.W. Chu (Eds.), *Diversity, Divergence, Dialogue*. iConference 2021 (pp. 328-345). Lecture Notes in Computer Science, vol 12645. Springer, Cham, 2021.

[PS26] D. Pal, C. Arpnikanondt, S. Funilkul, and V. Varadarajan, ''User experience with smart voice assistants: The accent perspective,'' in *Proc. 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT'19)*, Kanpur, India, pp. 1-6, 2019.

[PS27] H. Chin, L. W. Molefi, and M. Y. Yi, ''Empathy is all you need: How a conversational agent should respond to verbal abuse,'' in *Proc. 2020 CHI Conference on Human Factors in Computing Systems (CHI'20)*, Honolulu, HI, USA, pp. 1-13, 2020.

[PS28] Y. Wu, J. Edwards, O. Cooney, A. Bleakley, P. R. Doyle, L. Clark, D. J. Rough, and B. R. Cowan, ''Mental workload and language production in non-native speaker IPA interaction,'' in *Proc. 2nd Conference on Conversational User Interfaces (CUI'20)*, Bilbao, Spain, pp. 1-8, 2020.

REFERENCES

- [1] J. Guichard, E. Ruane, R. Smith, D. Bean, and A. Ventresque, ''Assessing the robustness of conversational agents using paraphrases,'' in *Proc. IEEE Int. Conf. Artif. Intell. Testing*, Newark, CA, USA, 2019, pp. 55–62.
- [2] Nielsen Norman Group. (2020). *The User Experience of Chatbots*. [Online]. Available: https://www.nngroup.com/articles/chatbots/
- [3] M. Jain, R. Kota, P. Kumar, and S. N. Patel, "Convey: Exploring the use of a context view for chatbots,'' in *Proc. Conf. Hum. Factors Comput. Syst.*, Montreal, QC, Canada, 2018, pp. 1–6.
- [4] S. Katayama, A. Mathur, M. Van den Broeck, T. Okoshi, J. Nakazawa, and F. Kawsar, ''Situation-aware emotion regulation of conversational agents with kinetic earables,'' in *Proc. 8th Int. Conf. Affect. Comput. Intell. Interact.*, Cambridge, U.K., 2019, pp. 725–731.
- [5] Q. N. Nguyen and A. Sidorova, ''Understanding user interactions with a chatbot: A self-determination theory approach,'' in *Proc. 24th Amer. Conf. Inf. Syst. Digit. Disruption (AMCIS)*, New Orleans, LA, USA, 2018, pp. 1–5.
- [6] K. Panetta. (2016). *Gartner's Top 10 Strategic Technology Trends for 2017*. [Online]. Available: https://itango.eu/gartners-top-10-strategictechnology-trends-for-2017/
- [7] S. Lee, H. Ryu, B. Park, and M. H. Yun, ''Using physiological recordings for studying user experience: Case of conversational agent-equipped TV,'' *Int. J. Human Comput. Interact.*, vol. 36, no. 9, pp. 815–827, Feb. 2020.
- [8] F. Narducci, P. Basile, M. de Gemmis, P. Lops, and G. Semeraro, ''An investigation on the user interaction modes of conversational recommender systems for the music domain,'' *User Model. User-Adapted Interact.*, vol. 30, pp. 251–284, Mar. 2020.
- [9] R. Ren, J. W. Castro, A. Santos, and J. de Lara, "Collaborative modelling: Chatbots or on-line tools? An experimental study,'' in *Proc. Eval. Assessment Softw. Eng.*, Trondheim, Norway, 2020, p. 260 269.
- [10] DriftTM. (2020). *Why are Chatbots Important Chatbot Learning Center*. [Online]. Available: https://www.drift.com/learn/chatbot/why-arechatbots-important/
- [11] R. Ren, J. W. Castro, S. T. Acuña, and J. de Lara, "Evaluation techniques for chatbot usability: A systematic mapping study,'' *Int. J. Softw. Eng. Knowl. Eng.*, vol. 29, no. 11n12, pp. 1673–1702, Nov. 2019.
- [12] S. Greenberg and B. Buxton, ''Usability evaluation considered harmful (some of the time),'' in *Proc. 26th Annu. CHI Conf. Hum. Factors Comput. Syst.*, 2008, Art. no. 111120.
- [13] A. Seffah, M. C. Desmarais, and E. Metzker, "HCI, Usability and software engineering integration: Present and future,'' in *Human-Centered Software Engineering—Integration Usability in the Software Development Lifecycle* (Human-Computer Interaction Series), vol. 8, A. Seffah, J. Gulliksen, M. C. Desmarais, Eds. Dordrecht, The Netherlands: Springer, 2005, pp. 37–57.
- [14] K. Curcio, R. Santana, S. Reinehr, and A. Malucelli, ''Usability in agile software development: A tertiary study,'' *Comput. Standards Interface*, vol. 64, pp. 61–77, May 2019.
- [15] *Ergonomic Requirements for Office Work With Visual Display Terminals (VDTs)—Part 11: Guidance on Usability*, Standard ISO 9241-11 1998.
- [16] *Systems and Software Engineering—Systems and Software Quality Requirements and Evaluation (SQuaRE)—System and Software Quality Models*, Standard ISO/IEC 25010, 2011.
- [17] A. Abd-Alrazaq, Z. Safi, M. Alajlani, J. Warren, M. Househ, and K. Denecke, ''Technical metrics used to evaluate health care chatbots: Scoping review,'' *J. Med. Internet Res.*, vol. 22, no. 6, Jun. 2020, Art. no. e18301.
- [18] S. Hobert, ''How are you, chatbot? Evaluating chatbots in educational settings - Results of a literature review,'' in *Proc. Gesellschaft Informatik*, N. Pinkwart, J. Konert, Eds. Phocis, Greece: DELFI, 2019, pp. 259–270.
- [19] A. Rapp, L. Curti, and A. Boldi, "The human side of human-chatbot interaction: A systematic literature review of ten years of research on text-based chatbots,'' *Int. J. Hum.-Comput. Stud.*, vol. 151, Apr. 2021, Art. no. 102630.
- [20] G. Tariverdiyeva and S. Borsci, "Chatbots' perceived usability in information retrieval tasks: An exploratory analysis,'' M.S. thesis, Behavioural, Manage. Social Sci., University of Twente, Enschede, The Netherlands, 2019.
- [21] N. M. Radziwill and M. C. Benton, "Evaluating quality of chatbots and intelligent conversational agents,'' 2017, *arXiv:1704.04579*.
- [22] K. Seaborn and J. Urakami, "Measuring voice UX quantitatively: A rapid review,'' in *Proc. CHI Conf. Hum. Factors Comput. Syst.*, Yokohama, Japan, vol. 416, May 2021, pp. 1–8.
- [23] C. Wohlin, P. Runeson, M. Hést, M. C. Ohlsson, B. Regnell, and A. Wesslen, *Experimentation in Software Engineering*, Berlin, Germany: Springer, 2012.
- [24] N. Juristo, ''Once is not enough: Why we need replication,'' in *Perspectives on Data Science for Software Engineering*, T. Menzies, L. Williams, and T. Zimmermann Eds. Burlington, MA, USA: Morgan Kaufmann, 2016, pp. 299–302, doi: [10.1016/B978-0-12-804206-9.00054-4.](http://dx.doi.org/10.1016/B978-0-12-804206-9.00054-4)
- [25] A. Santos, O. Gomez, and N. Juristo, ''Analyzing families of experiments in SE: A systematic mapping study,'' *IEEE Trans. Softw. Eng.*, vol. 46, no. 5, pp. 566–583, May 2020.
- [26] E. Fernéndez, O. Dieste, P. Pesado, and R. Garcéa, ''The importance of using empirical evidence in software engineering,'' in *Proc. Comput. Sci. Technol. Ser.*, G. Simani, and H. Padovani, Eds. Provincia de Buenos Aires, Argentina: Universidad de la Plata, 2011, pp. 181–189. [Online]. Available: https://digital.cic.gba.gob.ar/bitstream/handle/11746/4016/11746_ 4016.pdf-PDFA.pdf?sequence=1&isAllowed=y
- [27] V. R. Basili, F. Shull, and F. Lanubile, ''Building knowledge through families of experiments,'' *IEEE Trans. Softw. Eng.*, vol. 25, no. 4, p. 456 473, Jul/Aug. 1999.
- [28] G. Biondi-Zoccai, *Umbrella Reviews: Evidence Synthesis With Overviews of Reviews and Meta-Epidemiologic Studies*. Cham, Switzerland: Springer, 2016.
- [29] H. Cooper and E. A. Patall, ''The relative benefits of meta-analysis conducted with individual participant data versus aggregated data,'' *Psychol. Methods*, vol. 14, no. 2, pp. 165–176, Jun. 2009.
- [30] T. P. A. Debray, K. G. M. Moons, G. van Valkenhoef, O. Efthimiou, N. Hummel, R. H. H. Groenwold, J. B. Reitsma, and G. M. R. Group, ''Get real in individual participant data (IPD) meta-analysis: A review of the methodology,'' *Res. Synth. Methods, vo.*, vol. 6, no. 4, p. 293 309, Aug. 2015.
- [31] G. H. Lyman and N. M. Kuderer, "The strengths and limitations of metaanalyses based on aggregate data,'' *BMC Med. Res. Methodol.*, vol. 5, no. 1, pp. 1–7, Apr. 2005.
- [32] L. A. Stewart, M. Clarke, M. Rovers, R. D. Riley, M. Simmonds, G. Stewart, J. F. Tierney, and P.-I. D. Group, ''Preferred reporting items for a systematic review and meta-analysis of individual participant data: The PRISMA-IPD statement,'' *JAMA*, vol. 313, no. 16, p. 1657 1665, 2015.
- [33] B. A. Kitchenham, D. Budgen, and P. Brereton, *Evidence-based software engineering and systematic reviews*, vol. 4. Boca Raton, FL, USA: CRC Press, 2016.
- [34] K. Petersen, R. Feldt, S. Mujtaba, and M. Mattsson, "Systematic mapping studies in software engineering,'' in *Proc. 12th Int. Conf. Eval. Assessment Softw. Eng.*, Swindon, U.K., 2008, pp. 68–77.
- [35] R. P. Reyes, O. Dieste, E. R. Fonseca, and N. Juristo, "Publication bias: A detailed analysis of experiments published in ESEM,'' in *Proc. Eval. Assessment Softw. Eng.*, Trondheim Norway, 2020, pp. 130–139.
- [36] A. Ampatzoglou, S. Bibi, P. Avgeriou, and A. Chatzigeorgiou, ''Guidelines for managing threats to validity of secondary studies in software engineering,'' in *Contemporary Empirical Methods in Software Engineering*, M. Felderer and G. Travassos, Eds. Cham, Switzerland: Springer, 2020, pp. 415–441.
- [37] C. E. Anchundia and E. R. Fonseca, "Resources for reproducibility of experiments in empirical software engineering: Topics derived from a secondary study,'' *IEEE Access*, vol. 8, pp. 8992–9004, 2020.
- [38] K. L. Gwet, *Handbook of Inter-Rater Reliability: The Definitive Guide to Measuring the Extent of Agreement Among Raters*. Gaithersburg, MD, USA: Advanced Analytics, 2014.
- [39] J. Cohen, ''A coefficient of agreement for nominal scales,'' *Educ. Psychol. Meas.*, vol. 20, no. 1, pp. 37–46, 1960.
- [40] J. R. Landis and G. G. Koch, ''The measurement of observer agreement for categorical data,'' *Biometrics*, vol. 33, no. 1, pp. 159–174, Mar. 1977.
- [41] A. Jedlitschka and D. Pfahl, ''Reporting guidelines for controlled experiments in software engineering,'' in *Proc. Int. Symp. Empirical Softw. Eng.*, Noosa Heads, QLD, Australia, 2005, pp. 95–104.
- [42] K. Hornbák, "Current practice in measuring usability: Challenges to usability studies and research,'' *Int. J. Hum.-Comput. Stud.*, vol. 64, no. 2, p. 79 102, Feb. 2006.
- [43] J. Sauro and J. R. Lewis, ''Standardized usability questionnaires,'' in *Quantifying the User Experience*, 2nd ed. Boston, MA, USA: Morgan Kaufmann, 2016, pp. 185–248. [Online]. Available: https://www.sciencedirect. com/science/article/pii/B9780128023082000084?via%3Dihub
- [44] G. Upton and I. Cook, *A Dictionary of Statistics*. New York, NY, USA: Oxford, 2008, doi: [10.1093/acref/9780199541454.001.0001.](http://dx.doi.org/10.1093/acref/9780199541454.001.0001)
- [45] J. Sauro and J. R. Lewis, "An introduction to correlation, regression, and ANOVA,'' in *Quantifying User Experience*, vol. 10. Boston, MA, USA: Morgan Kaufmann, 2016, p. 277 320. [Online]. Available: http://www. sciencedirect.com/science/article/pii/B9780128023082000102
- [46] A. Rutherford, *ANOVA and ANCOVA: A GLM Approach*. Hoboken, NJ, USA: Wiley, 2011.
- [47] E. Adamopoulou and L. Moussiades, "Chatbots: History, technology, and applications,'' *Mach. Learn. Appl.*, vol. 2, Oct. 2020, Art. no. 100006.

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