Measuring and Clustering Heterogeneous Chatbot Designs

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Conversational agents, or chatbots, have become popular to access all kind of software services. They provide an intuitive natural language interface for interaction, available from a wide range of channels including social networks, web pages, intelligent speakers or cars. In response to this demand, many chatbot development platforms and tools have emerged. However, they typically lack support to statically measure properties of the chatbots being built, as indicators of their size, complexity, quality or usability. Similarly, there are hardly any mechanisms to compare and cluster chatbots developed with heterogeneous technologies.

To overcome this limitation, we propose a suite of 21 metrics for chatbot designs, as well as two clustering methods that help in grouping chatbots along their conversation topics and design features. Both the metrics and the clustering methods are defined on a neutral chatbot design language, becoming independent of the implementation platform. We provide automatic translations of chatbots defined on some major platforms into this neutral notation to perform the measurement and clustering. The approach is supported by our tool Asymob, which we have used to evaluate the metrics and the clustering methods over a set of 259 Dialogflow and Rasa chatbots from open-source repositories. The results open the door to incorporating the metrics within chatbot development processes for the early detection of quality issues, and to exploit clustering to organise large collections of chatbots into significant groups to ease chatbot comprehension, search and comparison.

CCS Concepts: • **Software and its engineering → Software design engineering**; *Extra-functional properties*; • **Computing methodologies** → *Natural language processing*.

Additional Key Words and Phrases: chatbot design, metrics, clustering, quality assurance, model-driven engineering

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1 INTRODUCTION

Conversational agents (also known as chatbots) have become a popular way to access all kinds of software services – like services for customer support, banking, tourism, health and e-commerce – using conversation in natural language [40, 61]. Their use is rising because they lower the entry

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barrier to the services and can be ubiquitously used from many channels – from web sites to social networks and intelligent speakers – without the need to install dedicated applications. Chatbots are also used to assist workers in different domains, like software engineering [29, 45].

In response to this demand, many platforms have been created to construct chatbots [48], like Google's Dialogflow [14], Amazon Lex [30], IBM's Watson [66], and Rasa [52], among many others. Overall, Gartner estimates that there are more than 2000 natural language technology providers, with a significant number of them offering facilities to create chatbots [20]. Many of these solutions are low-code platforms covering the design, deployment and operation of the defined chatbots. However, their support for quality assurance is generally limited [40, 48].

Since chatbots are a kind of software, their construction should follow sound software engineering principles. In this regard, some recent approaches [5–7, 15] propose methods and tools for testing chatbots. However, while testing is essential to ensure the quality of the resulting chatbot, it requires having a functional deployed chatbot, it demands a high effort for creating testing phrases and oracles, and it is time-consuming.

We claim that the use of metrics can help to guide and control the quality of chatbots throughout their development and maintenance, becoming a complement to testing. However, to our knowledge, there are hardly any metric proposals for chatbot designs. Metrics are an accepted mechanism for assessing and controlling properties of software products and processes [17]. Chatbot static metrics can be useful to detect potential problems related to user experience (e.g., complex conversation flows, hard-to-read chatbot answers); as indicators of chatbot complexity; to compare properties of heterogeneous chatbots (i.e., built with different technologies); to discover commonalities and cluster similar chatbots; and to understand how different implementation platforms can impact on the chatbot design. Ultimately, the availability of metrics may have notable impact on current chatbot development practices and tools, helping to increase the quality of chatbots and the efficiency of their production processes.

Moreover, the wide variety of tools with which chatbots are built makes it difficult to search and compare chatbots. This calls for mechanisms to measure the similarity or dissimilarity between chatbots – even if developed with different technologies – to understand their commonalities and enable searching for chatbots akin to a given one, e.g., as a first step towards the reuse of existing chatbots. While clustering techniques are suitable for this purpose [58], they have not been applied to chatbot designs yet.

To improve this situation, we propose a suite of 21 static metrics for chatbot designs, and two methods for clustering chatbots. The first method groups similar chatbot designs according to a selected set of metrics, which enables the identification of chatbots with (dis)similar design features (e.g., size, complexity of conversation paths, verbosity). This is useful, e.g., to classify chatbots according to their design properties; to discover potentially problematic chatbots; or to reason about the design features of large chatbot repositories (e.g., to analyse if chatbots built with different technologies have similar design characteristics). The second method performs a semantic clustering of chatbots along conversation topics, based on the frequency of the words appearing in the chatbot issued and expected phrases. This is useful, e.g., to identify chatbots on the same topic for their reuse; to facilitate the construction of recommender systems for chatbots; to organise large chatbot repositories according to their domain; or to facilitate chatbot search.

Both the metrics and the clustering methods are defined over a neutral design notation called Conga [46, 47]. This way, they become technology-independent and do not need to be reimplemented for each chatbot technology. Our proposal is available as a web platform named Asymob at http://miso.ii.uam.es/asymobService. Asymob features a chatbot repository, and provides importers from several chatbot platforms into our neutral design language to enable measuring and clustering chatbots developed with heterogeneous technologies. The platform is directed to two target groups.

First, chatbot developers, who can upload their chatbots (privately or publicly) into Asymob, so that they can be measured and compared against the other chatbots in the repository, built with the same or different technology. This way, developers can assess chatbot quality metrics during the development process, as well as search chatbots with certain design features or conversation topics, which can then be reused. Second, chatbot researchers, who can use our platform to analyse and compare characteristics of existing chatbot ecosystems built with diverse technologies. To assess our proposal, we report on an evaluation applying the metrics and the clustering methods over Dialogflow and Rasa chatbots retrieved from public repositories.

This paper is an extension of our preliminary works [9, 33]. Previously [9], we introduced a suite of 20 chatbot design metrics, proposed their technology-independent definition atop Conga, made their implementation available via an API, and evaluated their suitability on 12 chatbots. Subsequently [33], we developed a web interface to facilitate the usage of the API, and enabled clustering chatbots based on their metrics and vocabulary, in the latter case, using a simple bag-of-words model. The present paper extends these previous works as follows:

- We have refined our suite of metrics, including a new readability metric, and expanding the explanations and rationale of the metrics.
- We have improved our metrics-based clustering by using principal component analysis.
- We have improved our vocabulary-based clustering by applying stemming (which improves efficiency as it reduces the dimensionality of the chatbot vector representation), extracting descriptive terms for each chatbot cluster, and calculating the term frequency-inverse document frequency (TF-IDF) [57] of the chatbots' vocabulary (which improves our previous implementation based on bag-of-words by considering the importance of words according to their frequency of appearance).
- We report on a thorough, extended evaluation of the metrics on a dataset of 259 chatbots ($\approx 22x$ more than in our previous work [9]), which is available at https://github.com/asym0b/Dataset. To the best of our knowledge, this is the first large-scale evaluation of open-source chatbots reported in the literature.
- We detail a novel evaluation of our semantic clustering method.

The rest of this paper is organised as follows. Section 2 introduces the core concepts behind chatbots and motivates our work. Section 3 overviews related work. Section 4 introduces our proposed metrics suite, and Section 5 our two methods to cluster chatbots. Section 6 describes tool support. Section 7 reports on the results of our evaluation. Finally, Section 8 finishes with the conclusions and prospects for future work.

2 BACKGROUND AND MOTIVATION

This section provides some background on task-oriented chatbots (Section 2.1) and motivates our work (Section 2.2).

2.1 Background on task-oriented chatbots

Chatbots are conversational software systems with a natural language interface. They can work in open domains – like OpenAI's ChatGPT [42] or Google's Bard [21] – or be task-oriented. The latter are typically built to access existing software services like those in banking or shopping; or to automate human services, like those for customer support. In this work, we are interested in task-oriented chatbots.

Figure 1 shows a diagram with the typical working schema of a task-oriented chatbot. The user normally starts the interaction by providing an *utterance* – a phrase in natural language – via some channel (step 1). The interaction can be using text (e.g., if the chatbot is deployed on a social

network like Telegram[1]) or voice (e.g., if the chatbot is deployed on smart speakers like Amazon echo[2]). Then, the chatbot processes the utterance to give a proper response (step 6). This involves several steps, which we detail next.

First, the chatbot analyses the utterance to discover the user goals. For this purpose, most chatbots are designed around a set of *intents* (step 2 in the figure). These are conversation topics the chatbot aims at recognising, related to the offered functionality. Depending on the implementation platform, intents are defined either using *regular expressions* and *templates* (e.g., as in Pandorabots [43]) or with *training phrases* that become interpreted using natural language processing (NLP). Intents can also include *parameters*, identifying relevant information pieces to be extracted from the user utterances (step 3).

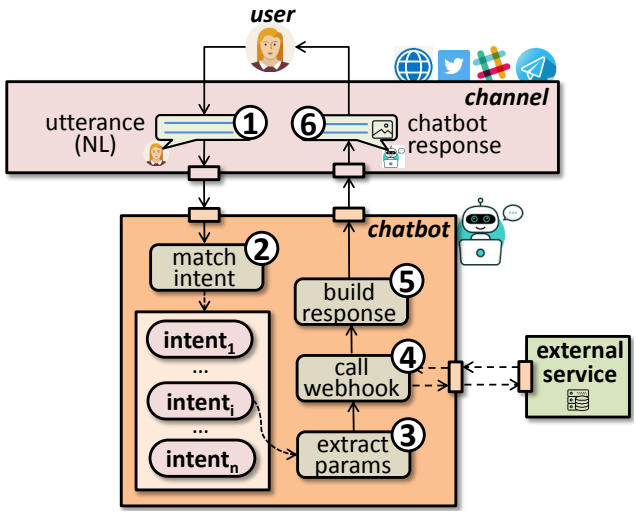


Fig. 1. Chatbot working schema.

As an example, a chatbot for a cafeteria would include an intent to recognise the users' orders. This intent would be activated upon a phrase like *"I'd like a medium cappuccino"*, from which the chatbot would extract two parameters: the type of drink (*cappuccino*) and its size (*medium*). If the parameters are mandatory, but the user does not provide them, the chatbot explicitly prompts the user for their value. Parameters are typed by *entities*, which can be either pre-existing in the platform (e.g., dates or numbers), or defined for a specific domain by the chatbot developer as a list of literals with synonyms (e.g., the type and size of drinks).

When the chatbot receives a user utterance, it matches the more likely intent. If no matching intent is recognised, the chatbot can trigger a *fallback* intent to ask for clarification. Otherwise, if an intent is matched, the chatbot performs the actions associated to the intent. These actions always include a text response (step 5), which may incorporate media elements (e.g., images, links) or widgets supported by the specific channel (e.g., buttons in Telegram). Other possible actions are accessing a backend service (e.g., to store the drink order, step 4) or performing a computation.

Finally, conversations are structured into *flows* that intertwine user utterances and chatbot responses. As an example, when the user says *"I'd like a medium cappuccino"*, the chatbot may answer *"Would you like something to eat?"*, leading to a new user interaction (e.g., *"No thanks"*), and so on, according to the defined conversation flow. Flows may bifurcate into different conversation *paths* depending on the user utterance.

Moore and Arar [37] propose a classification of chatbots based on their conversation style. *System-centric* chatbots answer user queries or interpret commands by means of two-turn conversations (i.e., each user turn starts a new conversation, and the chatbot lacks state). *Content-centric* chatbots provide a conversational interface for FAQs, typically supplying long document-like responses that may be unsuitable for voice-based interfaces or mobile devices with small screens. *Visual-centric* chatbots facilitate user interaction via buttons and other widgets, in a style borrowed from mobile phones. Finally, *conversation-centric* chatbots mimic human dialogs, offering conversation

[1] https://telegram.org/ [2] https://en.wikipedia.org/wiki/Amazon_Echo

management utterances (e.g., "*What do you mean?*") and short responses. This kind of chatbots are normally preferred because their conversation style suits a wider variety of devices and engages better in natural conversations.

Implementation-wise, most chatbot development tools support a declarative style of nearly all parts of the chatbot, sometimes complemented with imperative code. For instance, Rasa is a framework to develop chatbots using Python, markdown and YAML. A chatbot definition in Rasa comprises the following files: *config.yml*, which specifies configuration properties like the chatbot language or the used natural language prediction model; *data/nlu.md* declares the entities and the training phrases for the intents; *domain.yml* defines the chatbot intents, as well as the actions that the chatbot can perform (showing text messages, images, buttons, or custom actions defined in the Python file *actions.py*); and *data/stories.md* defines the conversation flows. Listings 1 and 2 in Section 6.2.2 show examples of some of these files. Once defined, a Rasa chatbot needs to be manually deployed on a server to become operative. In contrast, Dialogflow also has a declarative style to the construction of chatbots, but these are defined by means of forms through a low-code platform, and are directly hosted on Google Cloud. In addition, Dialogflow permits downloading the chatbot specification as a *zip* archive containing JSON files.

2.2 Motivation

Chatbot development should follow sound engineering principles, including early quality assessment. However, in early development stages, the chatbot may not be fully functional, making testing impossible. To overcome this problem, we propose design metrics that can be applied on chatbot designs – even if partially defined – and can help detecting quality issues. Among other issues, the proposed metrics can help detecting problems in the chatbot *conversation* (e.g., repeated or redundant conversation flows), the chatbot *responses* (e.g., responses that the users may find difficult to understand, or exceeding the limits of the deployment channel), or the chatbot *intents* (e.g., an intent with few training phrases, or two intents with similar training phrases). For example, an intent trained with the only phrase *"I'd like a medium cappuccino"* might not be able to recognise rewordings such as *"Would it be possible to order a regular capuchino?"*, hence frustrating the user. Metrics can help uncovering such issues prior to the chatbot deployment, hence contributing to assess the chatbot design maturity, to guide the design towards good practices, and to save effort in later development phases. Section 4.2 details the metrics and their potential impact on chatbot usability.

Nowadays, there are many heterogeneous chatbot development tools, as we illustrated above for Rasa and Dialogflow. Therefore, it makes sense to define the metrics over a neutral chatbot design language, so that they become independent of any chatbot development tool and can be reused. Section 4.1 introduces our proposal for such a neutral language, and Section 6.2 explains how to map it to Dialogflow and Rasa.

As in other software domains, chatbot development can benefit from reuse to achieve shorter times and higher quality. Clustering techniques can help in this respect, as they permit grouping objects (chatbots in our context) that are similar in some sense (e.g., having similar design features or conversation topics). Given a chatbot repository, a developer aiming to create a new chatbot could group the stored chatbots according to some criterion of interest (e.g., conversation topic), and then would pick a chatbot from one of the groups for its reuse (e.g., from a cluster containing chatbots for cafeterias, if that is the developer's goal). With this aim, Section 5 proposes novel semantic and metrics-based clustering mechanisms for chatbots. They are defined atop our proposed neutral chatbot design notation to make them applicable to chatbots of any chatbot development tool.

Finally, research on chatbots requires from repositories of chatbots that can be analysed and compared. Our tooling provides such facilities, and to benefit the community as much as possible, the tool is deployed publicly, and the datasets and code are released as open source.

3 RELATED WORK

In order to show the novelty of our contributions, this section reviews the state of the art on chatbot quality assessment (Section 3.1) and chatbot clustering (Section 3.2).

3.1 Chatbot quality assessment

Since the early days of conversational systems [67], researchers have proposed ways to evaluate their quality. For example, PARADISE [65] is an early framework for the evaluation of spoken dialogue agents, based on the correlation of performance and user satisfaction.

More recently, the popularity of chatbots has raised concerns on proper conversational design. For example, IBM's Natural Conversation Framework [38] relies on conversation patterns [39] and conversation design principles [37, 59], such as *recipient design* (i.e., provide multiple conversation paths for different user types), *minimization* (i.e., design concise chatbot answers), and *repair* (i.e., provide support for clarifications). In this line, *Chatbottest* [11] defined guidelines for identifying chatbot design issues in categories like answering, error management, intelligence, navigation, personality and understanding. This evaluation is enacted via the *Alma* chatbot, which interactively asks the chatbot designers about the features of interest. However, the burden is on the developer to manually test whether the chatbot fulfils the guidelines.

Literature reviews [44, 51] have also identified chatbot quality properties and ways to assess them. Radziwill and Benton [51] aligned chatbot quality attributes with the ISO-9241 notion of usability [22] (efficiency, effectiveness and satisfaction), while Peras [44] added further categories (e.g., information retrieval, affect). Generally, the assessment of these quality properties relies on the dynamic execution of the chatbot, on collecting statistical data, or on subjective evaluations [12, 18, 25, 36, 53].

In their survey, Motger et al. [40] identified some chatbot research challenges, like advanced testing features and analysis methodologies to improve chatbot quality attributes. In this line, some chatbot testing approaches have been proposed to assess chatbot quality and find defects. Tools like Botium [5] or OggyBug [15] support test automation, and some works target the generation of challenging test user utterances [6, 7]. ChatEval [60] targets testing readability, which can be done automatically by applying metrics – like BLEU2 and average cosine similarity [31] – to the chatbot responses, and interactively by launching tasks for human evaluation in Mechanical Turk.

Testing, being a dynamic technique, is complementary to our metrics, which are static and can be used earlier in the development process. Testing requires a functional chatbot, which usually entails having a backend (e.g., a service to which the chatbot sends requests) fully developed, whereas our metrics can be applied on partial, unfinished chatbot designs. Moreover, testing requires defining test scenarios with expected user utterances and chatbot replies, a burden that our metrics lack. In any case, metrics should not be seen as a substitute for testing, but as a complement to it.

Finally, the NLP community has developed useful readability metrics [31, 49] that can be applied to chatbots. Pitler and Nenkova [49] combined lexical, syntactic, and discourse features in a predictive model of human readers' judgements of text readability. This model associates features like the average number of verb phrases per sentence, the number of words in the text, and the vocabulary, with human assessments of how well a text is written. Liu et al. [31] evaluate metric weaknesses based on qualitative and quantitative results, and provide recommendations for future chatbot evaluation systems.

Table 1. Summary of chatbot quality assurance approaches.

Approach	Method	Nature	Aspects considered	Automated	Platform Independ.
Chatbottest [11]	Questionnaire	Dynamic	Answering, error management, intelligence, navigation, onboarding, personality, understanding	No	Yes
Radziwill and Benton [51]	N/A	Dynamic	Performance, functionality, humanity, affect, ethics & behaviour, accessibility	No	Yes
Coniam [12]	Human (indiv.)	Dynamic	Spelling, grammar	No	Yes
Jian and Ahuja [25]	Human (crowd)	Dynamic	Informativeness, fluency, humanlikeness	No	Yes
ChatEval [60]	Metrics, Human (crowd)	Dynamic	Readability	Yes	Yes
Finch et al. [18]	Human (indiv.)	Dynamic	Consistency, emotion, understanding, engaging, grammar, informativeness, quality, proactivity, relevance	No	Yes
MeMo [36]	Testing	Dynamic	Usability	N/A	Yes
Botium [5]	Testing	Dynamic	Functional correctness	Yes	Yes
OggyBug [15]	Testing	Dynamic	Functional correctness	Yes	Yes
Asymob	Design metrics	Static	Design size, conversation, outputs, expected inputs, vocabulary	Yes	Yes

Table 1 summarises the main approaches to chatbot quality assurance, classified with respect to the used method (testing, metrics, questionnaires, individual or crowd-based human evaluation), the nature of the method (static, dynamic), the chatbot aspects considered, the degree of automation, and whether the approach is independent of any chatbot tool. Most approaches treat the chatbots as black-boxes and require their execution (i.e., they are dynamic), so they cannot be applied at early design phases. Moreover, many of them rely on a subjective human judgement of the quality of the chatbot conversation. Overall, we observe a lack of static quality assurance mechanisms – like metrics – specific to task-oriented chatbot designs that can be evaluated statically, automatically, and independently of the chatbot implementation platform. Our goal is to fill this gap by proposing a white-box method able to perform measurements on chatbot designs.

3.2 Clustering techniques

A means to facilitate finding artefacts of interest (chatbots in our case) is to organise them into meaningful groups. This way, a developer who wants to create a new artefact can profit from reusing existing artefacts in a cluster of interest.

Clustering is an application of unsupervised machine learning to organise items according to some criteria (e.g., a concrete metric like the number of intents in case of clustering chatbots). Some popular clustering algorithms are K-means, hierarchical clustering [24] and density-based spatial clustering of applications with noise (DBSCAN) [16]. All of them must be configured with a distance measure. In addition, both K-means and hierarchical clustering require setting the number of clusters as hyperparameters, while DBSCAN has other parameters like the neighbourhood distance and the minimum number of points required to form a dense region.

Clustering has been used in several areas of software engineering [62]. For example, some works [27, 34] relied on clustering to analyse and provide insights on source code. For this purpose, these works derive topics from the vocabulary used in the code (i.e., identifier names, comments), and then use latent semantic analysis (LSA) to compute the linguistic similarity between source artefacts (i.e., functions, classes) and cluster them according to their similarity. In a similar vein, MUDABlue [26] used LSA to cluster (open-source) software systems along categories, which are determined automatically. As we will see, our semantic clustering uses similar concepts, but extracting the vocabulary from the chatbot phrases. In the chatbots field, Xu et al. [68] clustered

chatbot sessions based on similarity metrics at two levels: user responses and whole chat sessions. Their goal was providing feedback to the administrator to refine the chatbot logic. Instead, our goal is to use clustering to enable comparison of chatbot designs along similar design metrics or conversation topics.

Clustering has also been employed to organise model and meta-model repositories. For instance, Babür et al. [3] represented meta-models as vectors based on their vocabulary, and used hierarchical clustering to organise and visualise collections of models and meta-models. MDEForge [4] uses a similar approach to facilitate model search. AURORA [41] uses supervised machine learning to classify meta-models into a fixed set of categories. In our proposal to chatbot clustering, we use similar encodings and techniques, but focus on chatbot designs instead of meta-models.

Other approaches group software artefacts based on metric values. For example, Arshad and Tjortjis [2] used 7 metrics to cluster C# programs with the aim of identifying potential problems in the code. Zhong et al. [71] combined clustering with expert input (to inspect and label clusters) for analysing software quality. In this case, the clustering is based on 13 code metrics like lines of code, branch count, comments or cyclomatic complexity.

In summary, while both metrics and word embeddings have been used to obtain meaningful clusters of software artefacts, to the best of our knowledge, clustering for chatbot designs has not been studied yet in the literature. Moreover, we adapt two clustering techniques to chatbots: one based on design metrics, and another based on the chatbot vocabulary. Both techniques are complemented with methods aiming at explaining the results: principal component analysis in the first case, and a method to obtain the most descriptive terms of each cluster in the second.

4 MEASURING CHATBOT DESIGNS

In this section, we propose a suite of metrics tailored to chatbot designs. To define the metrics independently from the chatbot implementation technology, we use a neutral design notation to represent chatbots, over which the metrics can be computed. Section 4.1 starts by introducing the chatbot design notation, and then, Section 4.2 details our proposed metrics.

4.1 A neutral notation for chatbot designs: Conga

Since our aim is to develop metrics for chatbot designs, we need a concrete notation over which to define the metrics. For this purpose, we rely on the chatbot neutral notation we proposed in our previous work [46, 47], called Conga. We opt for this neutral notation since its definition is based on a thorough review of 15 widely used chatbot development platforms [46]. This means that the design concepts in Conga can be mapped from and to all these platforms. Hence, by defining the metrics over Conga, they become platform-agnostic as well as significant for many chatbot development platforms. As we will see in Section 6, another practical implication is that one can build importers from different platforms into Conga to measure and cluster existing chatbots built with different technologies.

Figure 2 depicts the meta-model of Conga. It permits representing a chatbot by a Chatbot object that contains a set of Intents, user-defined Entities, chatbot Actions, and conversation Flows. Conga supports multi-language chatbots (attribute Chatbot.lang), and so each intent can declare Training-Phrases per defined language. The phrases can include Parameters, declared on the intent defining the phrase. Parameters are typed either by predefined entities (enumeration PredefinedEntity) or by user-defined Entity objects. Entities can be Simple, Regex (regular expressions) or Composite, and for each language (EntityLanguage), they declare the literals and synonyms making up the entity. For example, a chatbot can declare a simple entity for drink sizes with literals small, medium and large in English, and additionally define synonyms regular for medium and big for large.

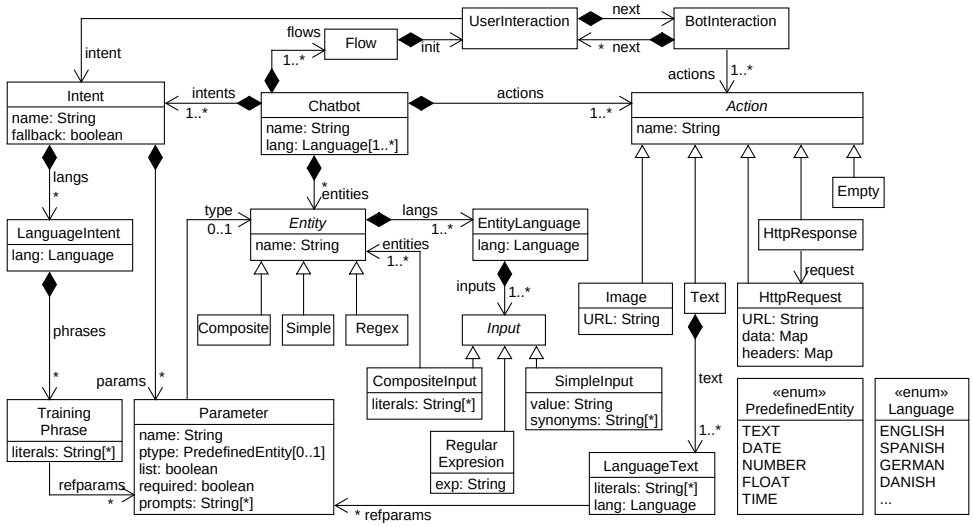


Fig. 2. Meta-model for chatbot design (from Cañizares et al. [9]).

A chatbot can define one or more Actions of type Image, Text, HttpRequest, HttpResponse and Empty. The first two types are used to compose responses combining images and text. HttpRequest and HttpResponse allow configuring the chatbot communication with external services in the backend. The Empty action is a wildcard for other platform-specific actions.

The conversation flow between the chatbot and the users is modelled by Flow objects consisting of user and chatbot turns (classes UserInteraction and BotInteraction). The user turn has a reference to the intent to be recognised in the interaction (reference UserInteraction.intent). The bot turn specifies the actions that the chatbot must perform (reference BotInteraction.actions).

4.2 A metrics suite for chatbot designs

Table 2 shows our proposed suite of 21 metrics for chatbot designs. All metrics measure internal attributes of chatbots. Our guiding principles were to quantitatively measure (quantities, lengths) every aspect of the design (intents, parameters, flows, etc.), and to contribute metrics able to provide insights on the quality, tone, similarity and complexity of the textual elements (training phrases, chatbot responses, entities) used to define the chatbot. The latter are qualitative in nature, serving as a means to assess whether the chatbot outputs and expected user utterances suit the target users and the chatbot deployment channel, or to warn about intents that a chatbot may confuse because they declare similar training phrases. However, we do not consider our suite of metrics closed, but expect the community to contribute with new metrics in the future.

Overall, we considered three sources when designing these metrics:

- Some of them, like INT (the number of intents) or ENT (the number of user-defined entities), are calculated by taking statistics of concepts covered by the meta-model in Figure 2. Our previous analysis [46] shows that these concepts are common to many chatbot development frameworks.
- Some other metrics, like VPTP, READ and OPRE, have been adapted from the NLP literature [8, 19, 31, 49] to assess the readability of the chatbot responses, their estimated reading time, or the complexity of the expected user utterances.

Table 2. Chatbot design metrics. Column Dimension uses abbreviations for Effectiveness, efficiencY and Satisfaction.

Metric	Description	Type	Dimension
Global metrics			
INT	# intents	design size	E
ENT	# user-defined entities	vocabulary size	S
FLOW	# conversation entry points	conversation diversity	E
PATH	# conversation paths	conversation complexity	S,Y
CNF	# confusing phrases	bot understanding	E,S
SNT	# positive, neutral, negative output phrases	user experience	S
Intent metrics			
TPI	# training phrases per intent	topic complexity	E,S
WPTP	# words per training phrase	topic complexity	Y
VPTP	# verbs per training phrase	topic complexity	S,Y
PPTP	# parameters per training phrase	topic complexity	E
WPO	# words per output	readability	S,Y
CPO	# characters per output	readability	S,Y
VPOP	# verbs per output phrase	readability	S
READ	reading time of the output phrases	readability	Y
OPRE	output phrase readability	readability	S, Y
Entity metrics			
LPE	# literals per entity	vocabulary complexity	S
SPL	# synonyms per literal	vocabulary complexity	S
WL	word length	readability	Y,S
Flow metrics			
FACT	# actions per flow	bot response complexity	E,S
FPATH	# conversation paths per flow	conversation complexity	S,Y
CL	conversation length	conversation complexity	Y

- Finally, we use conversation design principles [37, 59], and Moore and Arar's classification of chatbots [37], to interpret the value of some metrics such as PATH (the number of conversation paths), FLOW (the number of conversation entry points) and WPO (the number of words per chatbot output).

Our metrics can be used within software quality models such as the product quality model of the ISO/IEC 25010:2011 [23]. Our internal metrics target the chatbot design, which influences the *quality in use* of the system, but enable an early assessment. In particular, the fourth column of Table 2 classifies the potential impact of the metrics on usability (as defined in the ISO 9241-11 [22]) in terms of Effectiveness (i.e., accuracy and completeness with which users achieve their goals), efficiencY (i.e., time and resources that users expend to achieve their goals) and Satisfaction (i.e., comfort and acceptability of use). This mapping of metrics to quality properties embodies the consensus among five experts (the authors) based on their experience in both software quality assessment and chatbots, as well as a thorough review of works on chatbot usability from experts in the literature. Table 2 also classifies metrics depending on their target: either global design properties, or specific aspects of intents, entities or conversation flows. Non-global metrics can be computed per element (intent, entity, flow) or averaged for all elements of a kind.

4.2.1 Global metrics. We start explaining *global metrics*. These measure the number of intents (INT), entities (ENT) and conversation flows (FLOW, PATH), and also include understanding and user experience metrics (CNF, SNT).

INT is an indicator of design size and functionality, since each intent contributes functionality offered to the user. The larger INT is, the more functionality the bot offers, potentially impacting effectiveness. ENT measures the size of the chatbot vocabulary and the conversation topic diversity,

which may affect satisfaction. FLOW counts the number of conversation entry points for users, being an indicator of conversation diversity. Since each entry point might correspond to a functionality, FLOW may impact effectiveness. PATH is a global metric that informs on the overall number of conversation paths the chatbot can take, which is an indicator of conversation complexity. If PATH=FLOW, all conversations are linear, while if PATH>FLOW, some conversation splits into several paths.

As an example, Figure 3 shows two small excerpts of chatbot designs conformant to the CONGA meta-model. The chatbot design (a) depicts a linear flow (i.e., FLOW=PATH=1). Linear flows enable simple conversations, typically request/response, which may indicate a system-centric chatbot [37]. The chatbot design (b) shows a conversation flow that splits after the bot interaction (FLOW=1, PATH=2). This kind of flows permits non-linear conversations with multiple turns and dialogue alternatives, typical of conversation-centric chatbots [37].

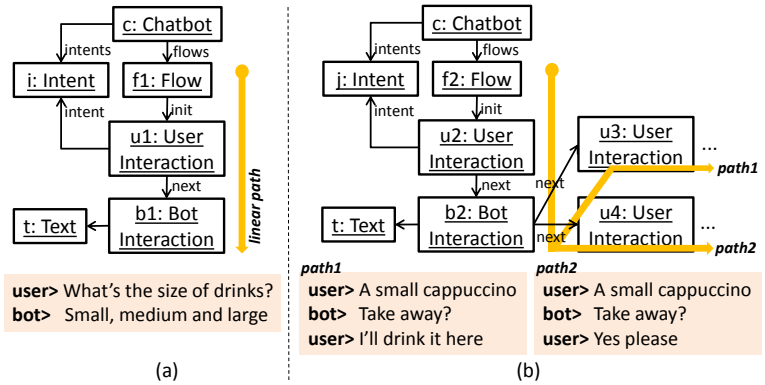


Fig. 3. Chatbot design excerpts illustrating (a) a linear conversation flow, (b) a forked conversation flow.

The combined use of FLOW and PATH can help detecting deviations of some conversation design principle. The *recipient* principle [59] advices to design for the target users, from experts (who may give all information at once) to novices (where the bot needs to prompt for more information). In turn, the *repair* principle [59] recommends supporting clarifications in the conversation, and multiple paths may be an indication of this. Moreover, having several paths per flow potentially results in more natural conversations (impacting satisfaction) but less predictable for the user (likely impacting the user effort or efficiency).

The CNF metric measures the semantic distance between the training phrases of different intents [10]. For this, the training phrases are tokenised and converted into 512-dimensional vectors using sentence embedding. Then, the semantic distance between two phrases is given by the cosine similarity between their embedding vectors. This metric is used to detect similar phrases that may confuse the bot to make it identify a wrong intent. Since this may cause errors, the metric is related to effectiveness and satisfaction.

The last global metric, SNT, measures the sentiment of the chatbot output phrases, classifying the phrases into positive, negative and neutral. This sentiment analysis uses a compositional model over trees based on deep learning [63]. Specifically, sentences are parsed into binary trees, where all leaves correspond to a word – represented as a vector – and each node receives a sentiment score. Then, the sentiment is calculated by recursive neural models that compute parent vectors in a bottom up fashion using several compositionality functions. The SNT metric is related to satisfaction, since a bot that outputs mostly negative phrases may cause a negative user experience [53].

4.2.2 Intent metrics. Intent metrics measure quality properties of each intent with respect to the expected user utterances and the bot output phrases.

Related to user utterances, TPI is the number of training phrases that an intent defines. The larger TPI is, the more precise the intent recognition might be, but this may also indicate a complex intent. WPTP measures the length of the training phrases in words. Long phrases are not adequate or even possible in social networks (e.g., Twitter restricts the message length), and are more difficult to understand for the chatbot. Therefore, large WPTP values might be problematic. VPTP measures the number of verbs per training phrase. This is an indication of interaction complexity, since composite phrases with several verbs can be more difficult to elaborate for the user [49]. PPTP counts the number of information items (i.e., parameters) the user needs to provide in a phrase, and high values signal intents involving complex domain concepts.

Regarding chatbot outputs, WPO measures the number of words per chatbot output. According to the *minimization* principle [37], the bot answers should be concise. Large phrases are more difficult to understand and can be problematic in social networks. The latter is more concretely targeted by CPO (characters per output), since high values may require scrolling (e.g., in mobile devices) and long reading times (with the risk that the user may not read the phrase completely [37]). Long outputs are especially problematic for voice-based chatbots, since speaking takes longer than reading [37]. Hence, large CPO values may decrease user satisfaction and efficiency. Similarly, VPOP is another indicator of the complexity of the bot responses, given by the number of verbs per output phrase. A chatbot can answer several phrases in a single output, and VPOP is computed for each phrase separately to better assess phrase complexity. READ gives an estimation of the reading time of the bot responses, which is related to efficiency. It is calculated as the ratio between the number of words per output, and the number of words that an average person can read per minute [8]. Finally, OPRE computes the readability of the chatbot responses using the Flesch Reading Ease Formula [19]. This metric yields a number ranging from 0 to 120, and the higher the number, the easier the chatbot responses are to read. Hence, OPRE may affect both satisfaction and efficiency.

4.2.3 Entity metrics. Entity metrics target user-defined entities representing domain concepts. LPE (literals per entity) and SPL (synonyms per literal) are indicators of the complexity of the concepts managed by a chatbot, impacting satisfaction. High LPE and SPL values signal elaborate concepts, but since SPL counts synonyms, a large number may improve recognition in user utterances (better satisfaction). A narrow vocabulary (low SPL) may constrain the way users communicate with the chatbot, and may lead to frustration if the chatbot does not recognise important parameters within user utterances. WL measures the length of words (i.e., the literals within the entities), and like CPO, it contributes to readability and may impact user satisfaction and efficiency.

4.2.4 Flow metrics. Flow metrics consider features of the conversation flows. FACT counts the bot actions (presenting images, text, calling backends) in each conversation flow. The more actions, the more sophisticated tasks can be achieved. Moreover, rich controls can help to reduce the user cognitive load and speed up the completion of the intended task. Hence, FACT may impact effectiveness and satisfaction.

FPATH measures the number of possible paths per conversation flow. High values signal complex conversations (i.e., more natural-sounding but less predictable). Note that, while the global metric PATH counts the overall number of conversation paths a chatbot can take, FPATH calculates the paths per each given flow. This way, PATH can be calculated by adding up FPATH for each flow.

Finally, CL measures the length of each path within a flow, as the number of bot and user turns. This is an indicator of conversation complexity. Longer paths require more time to complete – which affects efficiency – and are typical of conversation-centric chatbots [37].

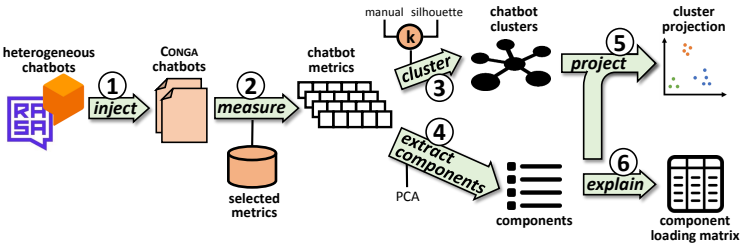


Fig. 4. Metrics-based clustering process.

5 CLUSTERING CHATBOTS

In this section, we propose two methods to cluster chatbots based on two disjoint criteria: metric values (Section 5.1) and chatbot vocabulary (Section 5.2). The former allows grouping chatbots by internal quality features (e.g., complex/simple conversations, large/succinct outputs). The latter groups chatbots by conversation topic.

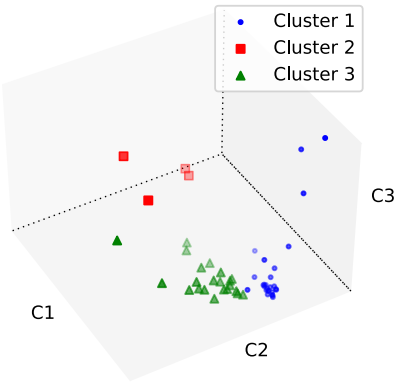
5.1 Metrics-based clustering

Metrics-based clustering is useful to identify groups of chatbots with (dis)similar design features. For this purpose, the chatbots are characterised based on the value of one or more metrics of interest. For example, clustering by metric INT (i.e., number of intents) would create groups of chatbots with similar size complexity, whereas if the user performs the clustering using metrics FLOW and PATH, then the chatbots would be grouped according to the complexity of their conversations.

Figure 4 shows the steps in our metrics-based clustering process. First, the process transforms the chatbots of interest into the CONGA neutral notation (step 1). Then, the user selects a subset of the metrics proposed in Section 4.2, which are applied to the chatbots (step 2). This way, each chatbot becomes represented by a vector of size n, where n is the number of metrics selected by the user, and each position of the vector contains the value of a selected metric for the chatbot. Next, the process calculates the clusters by applying the k-means algorithm on the chatbot metric vectors (step 3). The number of clusters to create (i.e., the k-value) can be either specified by the user or automatically computed using the silhouette coefficient [56]. Our process also performs a principal component analysis (PCA) of the metric vectors (step 4). PCA is a method to reduce the dimensionality of data while minimising information loss. In our case, it produces new variables (the components) that compress information of the metrics so that the first few components explain most of the variance of the metric values. We use PCA with two purposes. On the one hand, to project the clusters into a two or three-dimensional space for visualisation, by selecting the two or three principal components (step 5). On the other hand, to identify sets of related metrics (step 6). The latter is possible since PCA permits explaining how each metric contributes to each component, by providing the *loading* factor of the metric for the component. This effectively groups the metrics that contribute the most to each component.

As an example, Figure 5 shows the result of clustering a set of 54 chatbots[3] by using the metrics PATH, INT, FLOW, WL, PPTP and FPATH. In the graphic, each dot represents a chatbot, and the shape of the dot identifies the cluster where the chatbot belongs. Overall, the process yields 3 clusters with sizes 28, 4 and 22. The table in Figure 5 shows the average metric value for the chatbots in each cluster. At a first glance, one can see that clusters 1, 2 and 3 contain chatbots with low, high and medium values of PATH, INT and FLOW; low, medium and high values of WL and PPTP; and high, low and low values of FPATH.

[3] Dataset available at https://github.com/ASYM0B/SmallDataSet2.



	Cluster 1	Cluster 2	Cluster 3
Size (#chatbots)	28	4	22
PATH	7.18	88.75	11.05
INT	10.46	77.5	11.81
FLOW	3.54	73.25	9.77
WL	0	5.15	9.19
PPTP	0.21	1.13	1.55
FPATH	3.34	1.25	1.24

Fig. 5. Cluster projection into three dimensions, and average metric values for the chatbots in each cluster.

Table 3. Explained variance per component, and loading matrix, for the metrics and clusters in Figure 5.

	Components		
	C1	C2	C3
Explained variance (%)	48%	27%	16%
Cumulative explained variance (%)	48%	75%	91%
Loading matrix			
PATH	0.58		
INT	0.57		
FLOW	0.57		
WL		0.66	
PPTP		0.63	
FPATH			0.88

Table 3 shows the first three components found by PCA, their eigenvalues (the percentage of variance they explain), and their loading factors (the table omits factors lower than 0.42). The results confirm our previous intuition: the first component (C1) aggregates metrics PATH, INT and FLOW; the second one (C2) aggregates WL and PPTP; and the third (C3) includes FPATH. These three components explain 91% of the variance (cf. cumulative explained variance).

The projection in Figure 5 uses these three components to provide a position to each chatbot in a three-dimensional space. Roughly, the C1 axis positions chatbots according to their PATH, INT and FLOW metric values; axis C2 according to WL and PPTP; and axis C3 according to FPATH.

We can interpret this information to summarise the chatbots that are in each cluster. Specifically, the first component (C1) distinguishes cluster 2 from clusters 1 and 3. The metrics with the highest weight in C1 are PATH, INT and FLOW, which measure the conversation flow paths, the intents, and the conversation entry points. The table in Figure 5 shows that cluster 2 has the highest values for these metrics, so we conclude that the chatbots in this cluster are bigger than the rest, in the sense that they take into account more conversational contexts. Looking again at Figure 5, we can see that the second component (C2) separates clusters 1 and 3. The metrics that impact C2 the most are WL and PPTP, which measure the average word length of entities and the parameters per training phrase. We observe that the chatbots in cluster 1 have very low values for these metrics. In particular, they have zero words per entity, likely because most of them are defined using Rasa, where entities can be implicitly defined in Python code, and not caught by our Conga model.

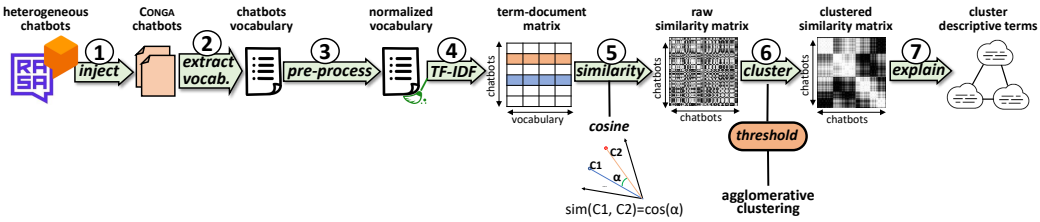


Fig. 6. Vocabulary-based clustering process.

In summary, cluster 2 contains complex chatbots, cluster 1 contains Rasa chatbots, and cluster 3 includes the rest of chatbots.

5.2 Vocabulary-based clustering

In addition to our metrics-based clustering, which groups chatbots depending on their internal design properties, we provide another clustering method based on the chatbot conversation topics. For example, chatbots for ordering food are likely to be in the same cluster, since their vocabulary is similar. For this purpose, we use a technique similar to Latent Semantic Analysis (LSA) [28] to compute the distance between chatbots.

Figure 6 describes our process for vocabulary-based clustering. The input to the process is a set of chatbots, which may have been developed with different technologies. Then, the process performs the following steps.

(1) **Inject.** The first step is the same as for metrics-based clustering, and transforms the chatbots into the CONGA neutral notation.
(2) **Extract vocabulary.** Next, the process extracts the vocabulary that each chatbot uses. This is made of the training phrases of the intents, the chatbot output phrases, and the literals and synonyms in entities.
(3) **Pre-processing.** The extracted vocabulary is tokenised to retrieve the words in phrases, and then normalised as follows. Stop words such as prepositions, articles and conjunctions are removed, since they do not provide relevant information. Moreover, the *Porter2* stemming algorithm [50] is applied to the words to keep just their morphological root (i.e., the stem). This way, two words that only differ in their inflected forms are considered equal. Overall, stemming reduces the dimensionality of the chatbot vector representations, and it is useful for our purposes since it permits considering two chatbots using the same stemmed words as similar.
(4) **TF-IDF.** Next, to quantify the relevance of a word to a chatbot, the process computes the term frequency-inverse document frequency (TF-IDF) [57]. This is one of the most popular term-weighting methods today, widely used in information retrieval, text mining and analysis, and clustering of source code [27]. Specifically, each chatbot C is represented as a vector, where each position in the vector represents a (stemmed) word w, and contains the weight $W(w, C)$ of the word w for the chatbot C. This weight is calculated considering the frequency $f(w, C)$ of the word w in the chatbot C and in the set of chatbots $\mathcal{R}$ to be clustered, as given by the formula:

$$W(w,C) = \frac{f(w,C)}{max\{f(t,C) \mid t \in C\}} \cdot log\left(\frac{|\mathcal{R}|}{|\{D \in \mathcal{R} \mid w \in D\}|}\right) \quad (1)$$

A word w receives a high weight when w has a high appearance frequency in the given chatbot C, and a low appearance frequency in the whole set of chatbots R. Hence, the weights

tend to filter out common terms. Note that the weight vector of small chatbots may have many zeros.

Overall, the output of this step is a term-document matrix, where each row corresponds to a chatbot, each column corresponds to a (stemmed) word, and each cell of the matrix contains the TF-IDF weight of a word for a chatbot. Other chatbot representations, such as bag-of-words, or embeddings like Word2Vec [35], are also possible. We experimented with the former representation in previous work [33] (with worse results than using TF-IDF, as Section 7.5 will show). Using Word2Vec would require a very large corpus of chatbots for training, and it is left as future work.

(5) **Similarity.** The term-document matrix is used to measure the similarity between each two chatbots. For this purpose, we use the cosine similarity, which computes the angle between the vectors representing the two chatbots. To optimise this computation, each TF-IDF vector is normalised so that the only operation to do is multiplying the weights of each word. The cosine similarity yields a number between 0 and 1. Chatbots having analogous conversation topics will have a similarity close to 1, while chatbots of very different domains will obtain a low similarity tending to 0.

(6) **Cluster.** Next, our process uses agglomerative clustering [55] to group the chatbots based on their vocabulary-based similarity. This algorithm relies on a notion of distance. In our case, the distance d between two chatbots C_1 and C_2 is defined as $d(C_1, C_2) = 1 - sim(C_1, C_2)$, where $sim(C_1, C_2)$ is the cosine similarity of the chatbots. The algorithm creates clusters by merging successively the two nearest chatbots C_1 and C_2 to yield a new element C_{12}. The distance $d(C_{12}, C_3)$ from this new element C_{12} to another chatbot C_3 is defined by $d(C_{12}, C_3) = \frac{d(C_1,C_3)+d(C_2,C_3)}{2}$. This way, at each iteration, the algorithm removes the entries corresponding to C_1 and C_2 from the distance matrix, and adds a new element C_{12}. The algorithm stops when there are no more elements with a distance less than a given threshold t. This step yields two outputs: a clustered similarity matrix having chatbots as rows and columns, where each position (i, j) in the matrix contains the distance (a value between 0 and 1) between chatbots i and j; and a dendrogram with the cluster hierarchy.

(7) **Explain.** To understand the obtained clusters, a final step extracts the most descriptive terms for each cluster. A term is descriptive with respect to a cluster if it has a high appearance frequency in the cluster, in comparison to its frequency in the whole corpus of chatbots. Formally, we define the importance I of a term t in a cluster C with respect to the set of chatbots $\mathcal{R}$ as:

$$I(t)_{C,\mathcal{R}} = \frac{1}{|C|} \sum_{C \in C} W(t, C) - \frac{1}{|\mathcal{R}|} \sum_{C \in \mathcal{R}} W(t, C)$$

where $W(t, C)$ is the weight of the term t for the chatbot C in the term-document matrix (cf. Equation 1). This way, the importance of a term for a cluster is greater the more it appears in the cluster, and the less it appears in the chatbots outside the cluster.

As an example, Figure 7 shows the clustered similarity matrix resulting from step 6 for a set of 54 chatbots[4]. The matrix uses colours to represent chatbot similarity, where higher similarities (i.e., lower distance values) are depicted with darker colours. In addition, the figure represents the grouping of clusters by means of dendrograms. The number of clusters can vary depending on the used threshold. For example, a threshold of 0.87 yields 17 non-singleton clusters.

Table 4 shows the size of the eight biggest clusters, as well as their five most representative terms obtained as explained in step 7[5]. These terms enable recognising common topics of the chatbots

[4] Dataset available at https://github.com/ASYM0B/SmallDataSet. This dataset is different from the one used in the example of Section 5.1, as it serves to illustrate better vocabulary-based clustering. [5] Additionally, there are nine clusters with size two, and the rest are singletons.

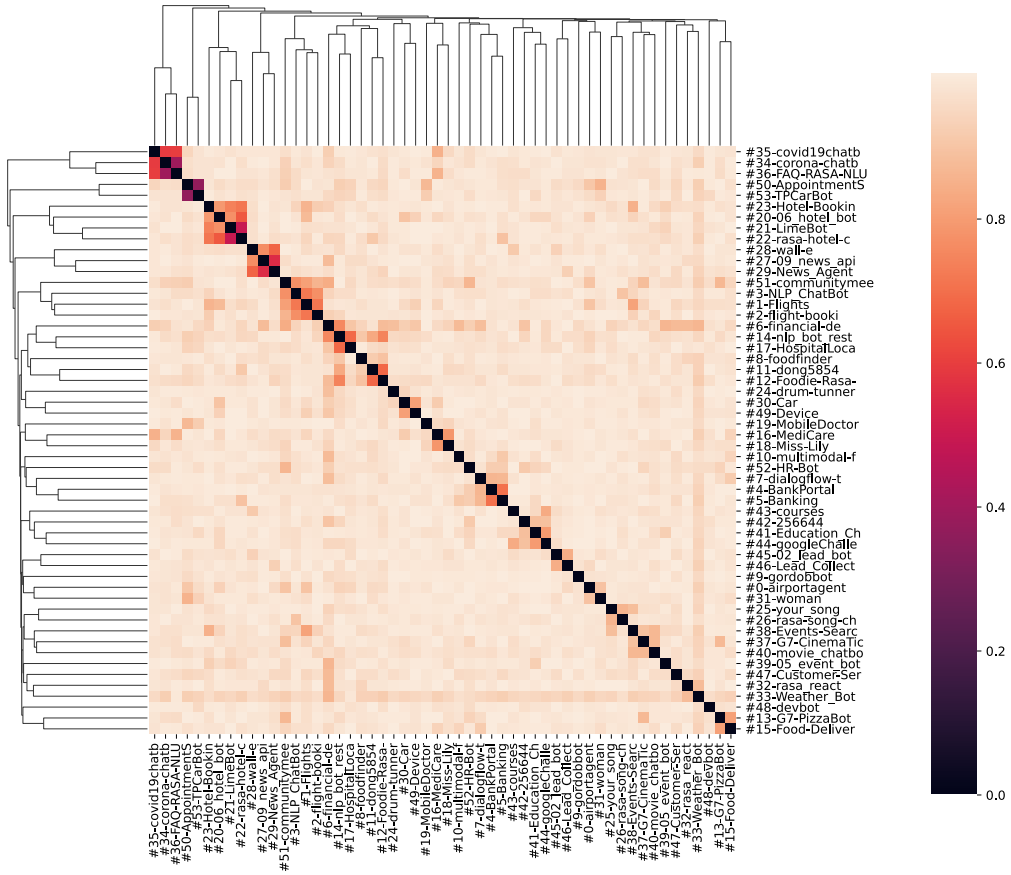


Fig. 7. Clustered similarity matrix of chatbots. Each cell represents the distance between two chatbots by colour intensity, where darker colours mean lower distance (i.e., higher similarity).

Table 4. Most descriptive (stemmed) terms in the eight biggest clusters.

		Top terms				
Clusters	**Size**	#1	#2	#3	#4	#5
Cluster 1	4	restaur	food	indian	north	serv
Cluster 2	4	transact	payment	transfer	pay	account
Cluster 3	4	student	graduat	bachelor	ec	faculti
Cluster 4	4	room	book	hotel	reserv	breakfast
Cluster 5	4	flight	return	leav	travel	book
Cluster 6	3	virus	corona	covid	spread	coronavirus
Cluster 7	3	news	headlin	latest	bbc	australia
Cluster 8	3	ticket	movi	concert	theater	cinema

that belong to a same cluster. For example, we can guess that the clusters contain chatbots related to restaurants (cluster 1), banking (cluster 2), teaching (cluster 3), hotels (cluster 4), air travel (cluster 5), covid (cluster 6), news (cluster 7) and leisure (cluster 8).

6 TOOL SUPPORT

We have built a tool called Asymob supporting the measurement and clustering of chatbot designs specified with Conga. The tool is deployed as a web platform at http://miso.ii.uam.es/asymobService. Its code is open source and available at https://github.com/PabloCCanizares/asymob.

Next, Section 6.1 presents the architecture of Asymob, including its main features and underlying technologies; Section 6.2 details the conversion of chatbots implemented in two mainstream platforms (Dialogflow and Rasa) into Conga; and Sections 6.3 and 6.4 describe the usage of the tool for chatbot measurement and clustering.

6.1 Overview of Asymob

Asymob supports *uploading* chatbot specifications of heterogeneous technologies into a common repository. Such specifications can be either a *zip* file containing the chatbot implementation (e.g., a Rasa project, Dialogflow JSON files) or a Conga model in XMI format [64]. The uploaded chatbots are then *measured* using the metrics presented in Section 4.2. Asymob provides *statistics* of the metrics across all chatbots in the repository. In addition, users can *query* the repository to search for chatbots within certain metric bounds and *compare* them against each other according to their metric values. The platform also allows *clustering* chatbots by their metric values (cf. Section 5.1) or by the conversation topics as given by the words appearing in their training phrases, chatbot responses and entities (cf. Section 5.2).

Figure 8 depicts the architecture of Asymob. Its functionality is offered via a web interface, which interacts with a service layer via a REST API. The *front-end* is implemented in HTML and JavaScript, and supports the interactive presentation of metrics and clusters using the libraries Plotly[6] and Cytoscape[7], while word clouds for describing chatbots and clusters are visualised with JQCloud[8].

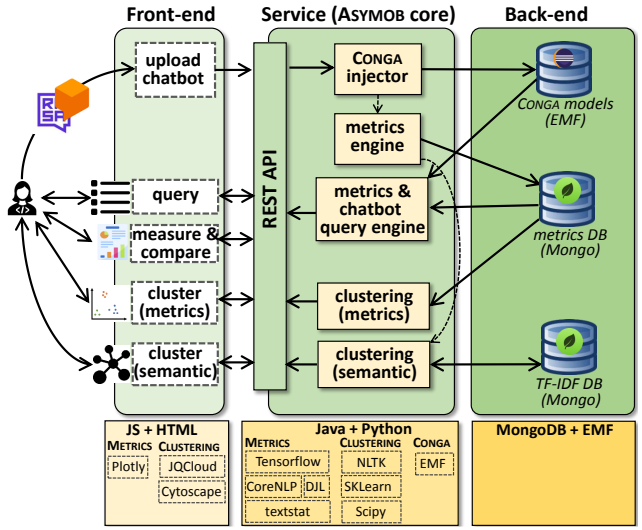


Fig. 8. Architecture of Asymob.

The *service layer* (the Asymob core) implements the functionality related to measuring and clustering chatbots. This core has an extensible design, which makes it easy to add new types of metrics, clustering criteria and chatbot technologies. To support chatbots from different platforms,

[6] https://plotly.com/ [7] https://cytoscape.org/ [8] https://mistic100.github.io/jQCloud/

it relies on the neutral chatbot design notation Conga, introduced in Section 4.1. Conga is built atop the Eclipse Modeling Framework (EMF) [64]. This way, Asymob computes the metrics on Conga models, independently of any chatbot implementation platform. To measure chatbots from a specific platform, an importer from the platform into Conga must be provided. Currently, Asymob has importers from Dialogflow and Rasa. Section 6.2 provides more details about these two importers.

Asymob supports some third-party technologies to simplify the implementation of new metrics. Specifically, it uses the library Stanford CoreNLP[9] to perform sentiment and syntactic analysis of the chatbot training and output phrases. The metrics SNT and VPTP use this library. In addition, Asymob uses textstat[10] – a Python library to obtain statistics from text – to calculate the metric OPRE, as well as Deep Java Learning (DJL)[11] and TensorFlow[12] to detect confusing phrases between intents using the cosine similarity and calculate the metric CNF based on this algorithm. The chatbot clustering functionality uses other Python libraries like NLTK[13], SKLearn[14] and SciPy[15].

The service layer has a REST API, which we have used to create the web platform (i.e., the front-end). This API also permits integrating our services in custom chatbot construction platforms, or within custom in-house development workflows (e.g., using Github actions, continuous integration servers like Jenkins, or DevOps processes).

An additional *backend layer* provides persistence. This stores the uploaded chatbots in the filesystem of the machine where the Asymob core is deployed, and uses MongoDB[16] for storing the data produced in the service layer (i.e., the metric values and the information required for conducting clustering).

As Figure 8 shows, when a chatbot is uploaded into the platform, it is converted to Conga and immediately measured, storing the results in a MongoDB database. In addition, the TF-IDF frequency of each word in the chatbot is calculated and stored in a database as well. These are background processes that do not slow down the uploading process, but reduce the response time of future requests of chatbot measurement, comparison and clustering.

6.2 Importing chatbots into Conga

Next, we provide details of the importers that Asymob provides to convert chatbots from two representative and widely used chatbot platforms (Dialogflow and Rasa) into Conga.

6.2.1 Importer from Dialogflow to Conga. Dialogflow [14] is a low-code development platform to create chatbots using a graphical interface within the browser. Chatbots so defined can be exported as JSON files, which our importer converts into Conga models.

In the JSON-based representation of a Dialogflow chatbot, the file *Agent.json* describes global chatbot features, like its name, definition languages, or connection data to external services (the *webhook*). The latter include details such as the URL of the service, headers, and authentication credentials. Our importer creates a Conga Chatbot object using the agent's name and languages, and an HttpRequest action with the webhook data.

Entities in Dialogflow can be predefined or user-defined. The latter data are described either by a regular expression, a list of literals with synonyms, or a composite entity. Each user-defined entity becomes exported as a JSON file containing the entity name and configuration information (if it is a regular expression or a composite entity), and one file per definition language with the corresponding literals. Our importer converts these files into Conga Entity objects.

Intents in Dialogflow have a name, training phrases, responses, parameters, and an indication of whether they are fallback or enable a webhook, among other features. Intents are exported

[9] https://stanfordnlp.github.io/CoreNLP/ [10] https://pypi.org/project/textstat/ [11] https://djl.ai/
[12] https://www.tensorflow.org/ [13] https://www.nltk.org/ [14] https://scikit-learn.org/ [15] https://scipy.org/
[16] https://www.mongodb.com/

```
## intent:order
- I'd like a [medium]{"entity": "size", "value": "medium"} [cappuccino](type)
- I want a [small]{"entity": "size", "value": "small"} [latte](type)
- Can I order a [large]{"entity": "size", "value": "large"} [black](type) coffee?
## synonym:small
- little
- short
## synonym:medium
- regular
- median
## synonym:large
- big
- extra
```

Listing 1. Example of *data/nlu.md* Rasa file

```
## story1
* order
    - utter_confirm_order
```

Listing 2. Example flow from *data/stories.md* Rasa file

into JSON files. For each intent definition file, our importer creates a Conga Intent object with its Parameters and TrainingPhrases, as well as the necessary Actions to compose each response. We currently support text and image responses, and convert other custom responses into Empty actions (but this does not affect the defined metrics).

Finally, Dialogflow controls the conversation flow via contexts. These can be input/output to intents, and can store relevant conversation state. Our importer uses the contexts and the responses of the related intents to generate Conga Flow objects.

6.2.2 Importer from Rasa to Conga. Rasa [52] is a framework to develop chatbots combining Python, markdown and YAML. The definition of Rasa chatbots comprises several files. The *config.yml* file defines configuration properties, like the chatbot language or the used NL prediction model. The *data/nlu.md* file contains training phrases for the intents, together with entities and synonyms or regular expressions. As illustration, the *data/nlu.md* file in Listing 1 defines an intent called order (lines 1–4). The parameters in the training phrases are defined within square brackets and are followed by the entity name either in parenthesis (e.g., [cappuccino](type)) or within curly brackets (e.g., [medium]{"entity": "size", "value": "medium"}). The listing also declares synonyms for literals small (lines 5–7), medium (8–10) and large (11–13).

The file *domain.yml* defines the chatbot intents, entities and actions. Actions can be text, images, buttons, or custom actions defined in the Python file *actions.py*. Finally, the file *data/stories.md* specifies the conversation flows. Listing 2 shows a flow example, specifying that matching the intent order triggers the response utter_confirm_order.

We have built an importer that reads the chatbot language from the *config.yml* file and creates Conga intents and entities from the *data/nlu.md* file, Conga actions from the *domain.yml* file, and Conga flows from the *data/stories.md* file. As in the case of Dialogflow, our importer from Rasa supports text and image responses, and converts Rasa custom actions into Conga empty actions. As a limitation, entities in Rasa can also be defined using Python code, instead of using the declarative, explicit approach shown in Listing 1. In this case, our importer is not able to produce Conga entities, and signals this fact using a warning.

6.3 Measuring chatbots with Asymob

When a chatbot is uploaded, Asymob computes its metrics and displays their value in a table and also in interactive graphs that compare these values with statistics of the chatbots in the repository. Figure 9 shows the graph for metric INT. The left bar displays statistics of the chatbot repository, and the bar to the right displays the metric value for the uploaded chatbot. We observe that the new chatbot can be considered small since it has 4 intents, while the average number of intents of the chatbots is around 15 (with a median of 7). The computed metrics are persisted to speed up the generation of statistics when new chatbots are uploaded, and to facilitate the following functionalities.

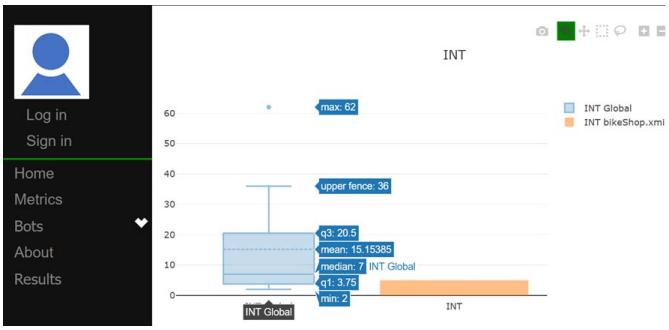


Fig. 9. Chatbot measurement.

First, Asymob offers statistics of the metrics of all chatbots in the repository (average, minimum, maximum, median and 1st and 3rd quartiles). They are displayed as a table, as a graph, and side-by-side with the metric values of a specific chatbot, as Figure 9 shows.

Asymob permits comparing a collection of chatbots based on a set of metrics selected by the user, as shown in Figure 10. In the upper graphic, the x-axis displays the selected metrics (13 in the figure), and the y-axis shows their value for the chatbots selected from the repository (10 bots in this case). The lower graphic permits zooming on the values for one of the selected metrics (bars to the right) and comparing them with the average metric value in the repository (bar to the left). In the figure, the user has zoomed on the values for metric INT. We can see that Car and recruitment-bot-rasa stand out in this metric, meaning that they have more conversation alternatives (intents). This comparison can also be performed for several versions of the same chatbot (if different versions were uploaded into the repository) to reason about the evolution between chatbot versions in terms of metrics.

The platform also includes a metric-based chatbot search facility, where users can specify the lower and upper limits for the value of some metrics of interest, and Asymob displays the chatbots in the repository with metric values within these boundaries. This is useful to obtain sets of chatbots with certain characteristics, e.g., simple chatbots with few intents and no defined entities, or complex chatbots with many intents and complex conversation flows.

6.4 Clustering chatbots with Asymob

Asymob supports the metrics-based and vocabulary-based clustering methods described in Section 5. In both cases, the user starts by selecting the chatbots to cluster. Then, the result depends on the clustering method.

In the case of metrics-based clustering, the tool displays the resulting clusters in a table and graphically, as Figure 11 shows. The graph can display two or three dimensions, so if the user selects

Fig. 10. Chatbot metrics comparison.

more than three metrics as clustering criteria, the platform reduces the number of dimensions using PCA. The graphic represents each chatbot as a dot, and uses a different colour for each cluster of chatbots. The graphic is interactive, supporting rotation, zooming, and visualisation of each chatbot name. In Figure 11, there are 4 clusters with 161, 82, 9 and 7 chatbots. A table displays the average of the selected metrics of each cluster. This page also enables the inspection of each cluster (displaying the chatbots within the cluster in a table), and the information of the PCA (explained variance and loading matrix).

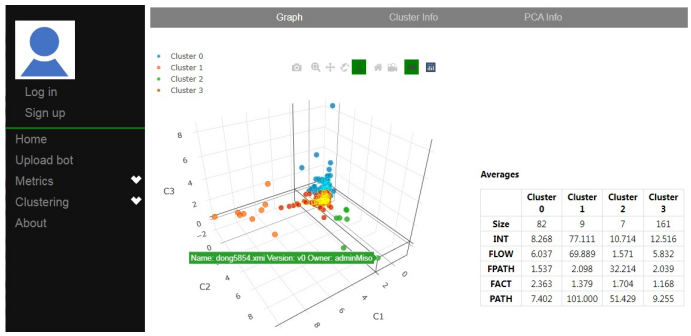


Fig. 11. Metrics-based clustering.

With regards to vocabulary-based clustering, in addition to the chatbots, the user can select a similarity threshold for the agglomerative clustering algorithm. Then, the resulting clusters are shown in a table, in an interactive hierarchical graph, and it is also possible to visualise the clustered similarity matrix on demand (cf. Figure 7). In the hierarchical graph visualisation, the first graph layer has a node per cluster, and clicking on a cluster shows the bots it contains. As an example, Figure 12 shows the chatbots within a cluster, and a word cloud with the most frequent words of the chatbots in the cluster. The most relevant words for the cluster can also be displayed on a table. The width of the edges in the graph is proportional to the similarity between the two connected chatbots. Clicking on a chatbot displays its metrics on a table.

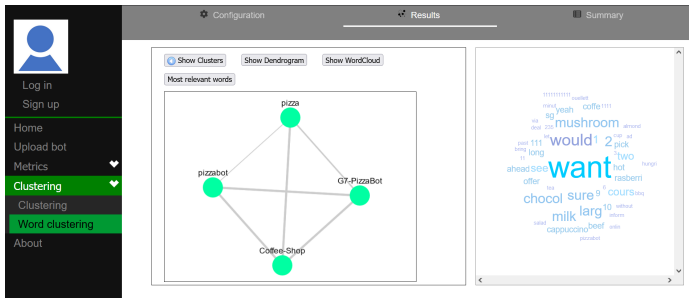


Fig. 12. Vocabulary-based clustering.

7 EVALUATION

This section reports on an empirical study whose goal is assessing the usefulness of our metrics and the efficacy of our vocabulary-based clustering. First, Section 7.1 overviews the followed research methodology and states the research questions (RQs). Then, Section 7.2 describes the experiment setting, and Sections 7.3–7.5 answer the RQs. Section 7.6 elaborates on threats to validity. Finally, Section 7.7 discusses the main findings in the studies, providing actionable insights for researchers, practitioners and tool builders.

7.1 Research methodology

Our evaluation aims to answer the following RQs:

RQ1 How do chatbots in the wild compare with respect to their size, conversation style, outputs, expected inputs and vocabulary?

RQ1.1 Do design metrics for Rasa and Dialogflow chatbots follow the same distributions?

RQ2 Can the defined metrics detect quality issues in real chatbots?

RQ3 Can the vocabulary-based clustering create meaningful groups of semantically related chatbots?

With this aim, we followed the research methodology depicted in Figure 13. Firstly, we created a dataset of Rasa and Dialogflow third-party chatbots, obtained from several relevant sources. Section 7.2 characterises this dataset. Then, we applied different research methods to answer each RQ.

The study of RQ1 aims to obtain a panorama of the features of chatbots in the wild, and RQ1.1 pursues to assess if metrics could serve as a means to analyse the impact of the used implementation platform in the features of the underlying chatbot designs. To answer both questions, we used Asymob to import the dataset of chatbots into Conga, and take measurements. Then, we compared different dimensions of the chatbots (size, conversation style, responses, expected user utterances and vocabulary) based on the chatbots' metric values. We also compared the minimum, maximum and average values of each metric per technology. Finally, we conducted some equality tests to analyse whether the metrics have the same probability distribution of values in Dialogflow and Rasa. Section 7.3 reports on this analysis.

The goal of RQ2 is to evaluate whether the proposed metrics can help to statically detect potential problems ("*bad smells*") in chatbot designs. We do not expect every discordant metric value to signal a real problem, but instead, we are interested in assessing the usefulness of metrics as an inexpensive chatbot quality assurance mechanism (e.g., compared to testing) that can be used early in the development process. To answer this question, we analysed the obtained measurements to identify statistical outliers for each metric (i.e., metric values that largely differ from the other metric values).

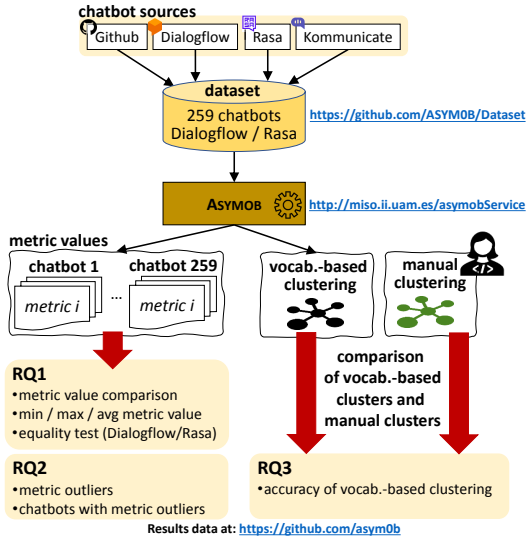


Fig. 13. Research methodology for our evaluation.

After that, we looked at the chatbots with outlier values for some metric, to identify whether these values signalled a design error. Section 7.4 identifies the metric outliers per technology, reporting the percentage of those that present problems.

Finally, the aim of RQ3 is evaluating the extent to which our semantic clustering can produce groups of chatbots that are meaningful. To answer this, we performed the clustering of all chatbots in the dataset using our vocabulary-based approach on the one hand, and manually on the other hand. Then, we computed the accuracy with which the vocabulary-based clusters mimic the manual clusters built by a human. Section 7.5 reports the results.

7.2 Experiment setting

The dataset for our evaluation contains as many Rasa and Dialogflow third-party chatbots as possible, coming from four sources: Github, Dialogflow, Rasa and Kommunicate[17]. The chatbots from Github were obtained via Github Search[18], using dedicated search queries for each technology. For Rasa, we used the following query, which searches software repositories containing some of the standard files in Rasa projects: *rasa AND (path:/stories.md OR path:/nlu.md)*. Similarly, the query to retrieve Dialogflow chatbots was *dialogflow AND (path:agent.json OR path:dialogflow*.zip)*. Then, we analysed the repositories returned by the queries, to assess that they actually contained chatbot definitions. Moreover, from the retrieved chatbots, we filtered out those that were malformed or were not defined for the English language. Note that we did not remove *toy* or incomplete chatbots, since one of our goals was to check whether our metrics could detect unfinished or partial designs (e.g., intents missing training phrases)[19]. Finally, to complement this set of chatbots, we added to our dataset all predefined chatbots that the platforms Dialogflow, Rasa and Kommunicate offer to their users.

Table 5 describes our dataset, available at https://github.com/asym0b/Dataset. It contains 259 chatbots, classified either as open source if they were located in an open-source repository, or

[17] https://www.kommunicate.io/ [18] https://github.com/search [19] The interested reader can find the results of our experiment for RQ2 without toy/incomplete chatbots in the dataset at: https://github.com/PabloCCanizares/asymob/tree/master/MetricsOutliers/Filtered

predefined if they were available as prebuilt agents in some platform. Predefined chatbots typically illustrate the platform capabilities in an application domain, and can be reused and modified to fit specific needs. The dataset is balanced in terms of technologies (117 Dialogflow chatbots, 142 Rasa chatbots), but predefined chatbots are a minority in the dataset (24 predefined chatbots, 235 open source chatbots).

Table 5. Description of the chatbots dataset.

Technology	Source	Kind	#Chatbots
Dialogflow	Github	Open source	96
	Dialogflow	Predefined	14
	Kommunicate	Predefined	7
Rasa	Github	Open source	139
	Rasa	Predefined	3
			259

7.3 RQ1 & RQ1.1: Chatbot comparison and metrics distribution across technologies

To answer RQ1 and RQ1.1, we applied the metrics suite to all chatbots in our dataset. The detailed metric values for each chatbot are available at https://github.com/asym0b/Dataset. Table 6 displays a summary of the results. The table shows the minimum, maximum, average and median values for each metric, distinguishing between Dialogflow chatbots, Rasa chatbots, or globally (i.e., considering Dialogflow and Rasa chatbots together). Intent, entity and flow metrics are calculated averaging the values over the number of intents, entities and flows in each chatbot. An exception is CL, which takes the maximum conversation length in the chatbot to be more informative. The sentiment metric SNT is disaggregated into positive (SNT^{+}), neutral ($SNT^{=}$) and negative (SNT^{-}). The last two columns of the table display the result of two nonparametric tests used to identify differences between the distribution of metric values in Dialogflow and Rasa (for RQ1.1, cf. Section 7.3.6).

Next, we exploit the metrics to compare the chatbots based on their size, conversation style, outputs, expected inputs, vocabulary (pertinent for RQ1) and implementation platform (RQ1.1).

7.3.1 Size. Metrics can be used to compare and classify chatbots based on their size. In particular, metric INT (number of intents) is a good indicator for chatbot size. Figure 14 shows the distribution of this metric across the chatbots' set, where the bars are divided between Rasa and Dialogflow chatbots. The global median is 8 intents, 90% of chatbots have less than 24 intents, just 13 chatbots (4%) have more than 40 intents, and 29 chatbots (11%) have 3 intents or less. Some of the smallest chatbots may be toy examples built to experiment with the technology, most frequently in Dialogflow.

7.3.2 Conversation. Metrics also serve to compare and classify chatbots based on their conversation style [37]. Some chatbots are prepared to hold a wider variety of conversations according to their number of intents (INT), conversation flows (FLOW) and conversation paths (PATH). Figure 15 projects the dataset along these three metrics. We observe that there is high correlation between the metrics (0.76 correlation between INT and FLOW, 0.62 between INT and PATH, and 0.69 between FLOW and PATH). Naturally, chatbots with more intents tend to have more flows, and therefore, more paths.

Conversations are fully linear in 46% of the chatbots (FLOW=PATH), and the remaining 54% chatbots support more complex conversations (FLOW<PATH). Most chatbots with linear conversations (69.2%) have medium-to-low size (8 intents or less). Figure 15 highlights the chatbot iLearn, as it is the largest chatbot with linear conversation, having 89 intents, flows and paths, and built using Dialogflow. Regarding chatbots with non-linear conversations, they have an average of 4.2

Table 6. Summary of metric values for the chatbots in the dataset.

Metric		Dialogflow				Rasa				Global				Equality tests	
Type	Name	Min	Max	Avg	Median	Min	Max	Avg	Median	Min	Max	Avg	Median	MW	KS
Global metrics	INT	1.0	89.0	10.9	6.0	2.0	143.0	15.4	9.0	1.0	143.0	13.37	8.0	$\leq 10^{-3}$	$\leq 10^{-3}$
	ENT	0.0	37.0	2.44	0.0	0.0	9.0	0.39	0.0	0.0	37.0	1.31	0.0	$\leq 10^{-3}$	$\leq 10^{-3}$
	FLOW	1.0	89.0	9.27	5.0	1.0	102.0	6.96	3.0	1.0	102.0	8.01	4.0	$\leq 10^{-3}$	$\leq 10^{-3}$
	PATH	1.0	117.0	10.51	5.0	1.0	207.0	15.04	7.0	1.0	207.0	13.0	6.0	0.029	0.070
	CNF	0.0	1606.0	87.42	3.0	0.0	10532.0	190.27	10.0	0.0	10532.0	143.81	7.0	$\leq 10^{-3}$	$\leq 10^{-3}$
	SNT^{+}	0.0	38.0	6.68	4.0	0.0	58.0	17.65	17.0	0.0	58.0	12.69	12.0	$\leq 10^{-3}$	$\leq 10^{-3}$
	$SNT^{=}$	0.0	100.0	47.38	64.0	34.0	100.0	73.55	73.0	0.0	100.0	61.73	70.0	$\leq 10^{-3}$	$\leq 10^{-3}$
	SNT^{-}	0.0	100.0	16.03	17.0	0.0	51.0	8.8	6.0	0.0	100.0	12.07	10.0	$\leq 10^{-3}$	$\leq 10^{-3}$
Intent metrics	TPI	0.0	94.67	9.04	5.56	0.0	235.17	18.46	8.09	0.0	235.17	14.21	6.75	$\leq 10^{-3}$	$\leq 10^{-3}$
	WPTP	0.0	9.62	2.72	2.41	0.0	5.37	3.03	2.83	0.0	9.62	2.89	2.75	0.007	$\leq 10^{-3}$
	VPTP	0.0	1.76	0.55	0.44	0.0	1.33	0.6	0.55	0.0	1.76	0.58	0.52	0.053	0.004
	PPTP	0.0	8.33	0.65	0.33	0.0	1.6	0.32	0.25	0.0	8.33	0.47	0.27	0.008	0.036
	WPO	0.0	23.11	6.02	5.79	2.25	87.63	9.37	6.63	0.0	87.63	7.86	6.27	0.001	$\leq 10^{-3}$
	CPO	0.0	125.56	27.23	23.56	10.82	440.1	43.87	28.4	0.0	440.1	36.35	26.06	$\leq 10^{-3}$	$\leq 10^{-3}$
	VPOP	0.0	3.56	0.91	1.04	0.17	3.52	1.26	1.2	0.0	3.56	1.1	1.12	0.004	$\leq 10^{-3}$
	READ	0.0	19.0	4.84	4.0	1.0	75.0	7.56	5.0	0.0	75.0	6.33	5.0	0.002	$\leq 10^{-3}$
	OPRE	0.0	92.0	54.69	75.0	44.0	113.0	89.3	89.5	0.0	113.0	73.67	84.0	$\leq 10^{-3}$	$\leq 10^{-3}$
Entity metrics	LPE	0.0	1177.13	22.06	0.0	0.0	0.0	0.0	0.0	0.0	1177.13	9.97	0.0	$\leq 10^{-3}$	$\leq 10^{-3}$
	SPL	0.0	7.13	1.25	0.0	0.0	0.0	0.0	0.0	0.0	7.13	0.57	0.0	$\leq 10^{-3}$	$\leq 10^{-3}$
	WL	0.0	36.0	3.87	0.0	0.0	0.0	0.0	0.0	0.0	36.0	1.75	0.0	$\leq 10^{-3}$	$\leq 10^{-3}$
Flow metrics	FACT	1.0	8.0	1.88	2.0	1.0	3.92	1.31	1.1	1.0	8.0	1.57	1.31	$\leq 10^{-3}$	$\leq 10^{-3}$
	FPATH	1.0	3.5	1.11	1.0	1.0	57.0	4.01	1.67	1.0	57.0	2.7	1.13	$\leq 10^{-3}$	$\leq 10^{-3}$
	CL	1.0	8.0	1.51	1.0	1.0	211.0	7.46	4.0	1.0	211.0	4.77	3.0	$\leq 10^{-3}$	$\leq 10^{-3}$

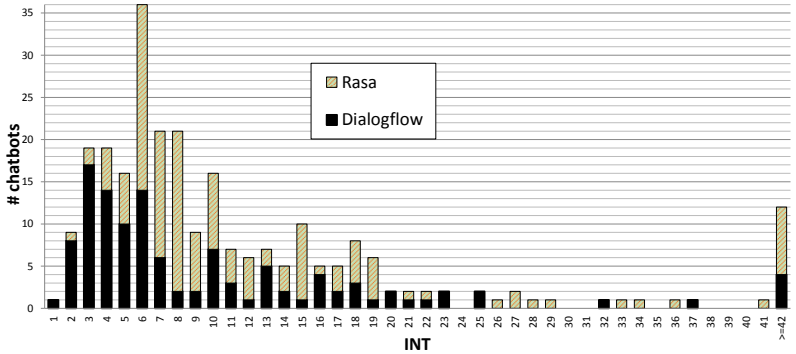


Fig. 14. Distribution of the number of INTents per chatbot.

paths per flow (average of $\frac{PATH}{FLOW}$, or FPATH[20]). As Figure 15 shows, some extreme cases include rasa-workshop-pydata-berlin (37 paths per flow) and dong5854 (57 paths in its unique flow). These chatbots feature very complex conversations, offering many choices to the user to continue the conversation, which might be confusing. Other big chatbots supporting non-linear conversations are more balanced, like finbot-master (41 intents, 22 flows, 207 paths, 9.4 paths per flow), Tiara-A-Chatbot (71 intents, 12 flows, 23 paths, 1.92 paths per flow) or identity-cloning-toolkit (114 intents, 102 flows, 115 paths). The latter chatbot is almost linear, with 1.13 paths per flow.

Additionally, Figure 16 shows the maximum conversation length (CL) of the analysed chatbots. In 92 chatbots, conversations are limited to one user-bot interaction (CL=1), and hence, they can be classified as system-centric [37]. Within this set, chatbots providing long responses are likely content-centric. Just two chatbots – nep-chatbot and FAQ_RASA_NLU – can be classified within this category. Both were built with Rasa and have over 54 words per output in average (WPO>54). Other chatbots allow longer conversations with more turns (CL>1). Chatbots with non-linear conversations (FLOW<PATH) have necessarily more than one turn (CL>1) and can be classified as

[20] In Table 6, FPATH is calculated for all chatbots, not only for those with non-linear conversations.

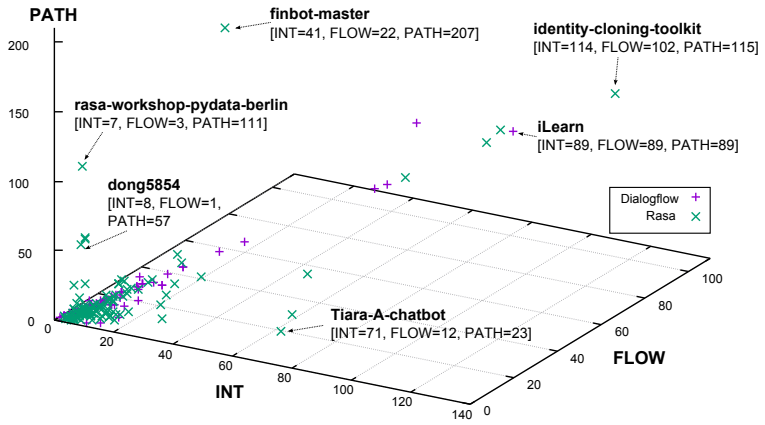


Fig. 15. Comparing chatbot conversation styles based on the distribution of INT, FLOW and PATH per chatbot.

conversation-centric [37]. In our dataset, the global median of CL is 3. Moreover, CL is 12 or less in 96% of the chatbots, and 6 or less in 84% of them.

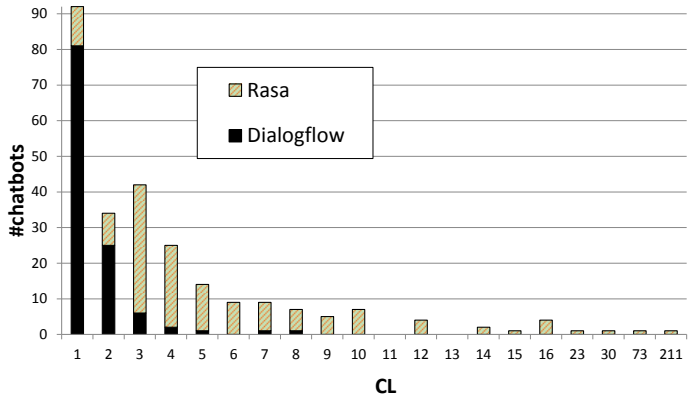


Fig. 16. Distribution of the chatbots' (maximum) conversation length (CL).

7.3.3 Outputs. Chatbots can be compared based on their responses to users. Interestingly, 35 chatbots (a 13.5% of the total) have no output phrases. In some cases – like the Car or Food-delivery predefined agents of Dialogflow – this is because the chatbot is a template agent that the developer needs to complete with custom outputs. In other cases – like the MysteryAnimal chatbot game built with Rasa – it is because a backend API generates the output dynamically.

Metrics WPO (words per output) and CPO (characters per output) help to compare the verbosity of the chatbots. The global median of WPO is around 6 words per output, and CPO is around 26 characters per output. These metrics take high values on verbose chatbots. For example, Tiara-A-Chatbot has over 87 words per output. As we will see in Section 7.4, this may indicate a quality problem. On the other end, two Dialogflow chatbots – fulfillment-temperature-converter and fulfillment-multi-locale – reply 2 words or less on average.

The OPRE metric captures the readability of phrases [19]. Its formula was designed to yield scores between 0 and 100, but it is possible to reach a maximum value of 120. The higher the value, the more readable the phrase. The dataset has a global average for OPRE above 73, which suggests easy-to-read output phrases in general. However, two chatbots – fulfillment-temperature-converter and fulfillment-multi-locale – have values of 17 and 35, hinting poor readability.

Regarding the sentiment of the output, we observe that, globally, most outputs have neutral tone ($SNT^{=}$ is 61.73%), while outputs with positive (SNT^{+}) and negative (SNT^{-}) tone are roughly equally distributed.

7.3.4 Expected inputs. Similarly as with the chatbot outputs, one can compare the complexity of the expected user inputs. Metrics WPTP and VPTP measure the words and verbs per training phrase. With a global average of 2.89 words and 0.58 verbs per phrase, chatbots generally expect uncomplicated user utterances. In addition, PPTP counts the number of parameters (i.e., pieces of information) that users should provide in each phrase. We find that 84 chatbots (32.4%) do not require users to provide any parameters (PPTP=0), 146 chatbots (56.3%) require an average number of parameters equal or less than 1 in user utterances (0<PPTP≤1), and only 29 chatbots (11.1%) expect more than 1 parameter in average, peaking at 8.33 parameters in the predefined chatbot template Dining-Out. Hence, chatbots are typically designed so that users have to provide very little information, if any, in each interaction.

With regards to the size of the training phrase set, TPI measures the average number of training phrases per intent. The global average is 14 phrases per intent. A total of 14 chatbots (5.4%) have a value of TPI equal or below 1, which may result in intent recognition problems when the chatbots are deployed. On the other extreme, 15 chatbots (5.8%) have an average of 50 training phrases or more per intent. This may signal complex intents that require many examples for accurate intent recognition, or overly specified intents.

7.3.5 Vocabulary. Entity metrics allow comparing the richness of the vocabulary that chatbots can recognise. Globally, 31% of the analysed chatbots define at least one entity (ENT>0). The average number of entities per chatbot is 1.31, with extreme cases of chatbots raising to 37 entities in Dialogflow (chatbot MysteryAnimal) and 9 in Rasa (chatbot Foodie-Rasa-Chatbot). High ENT values indicate a wide variety of domain-specific terms (e.g., animals in case of MysteryAnimal, or food types in case of Foodie-Rasa-Chatbot).

We can look deeper into each entity using metrics LPE (literals per entity), SPL (synonyms per literal) and WL (word length). These metrics are 0 in Rasa chatbots because Rasa can defer the recognition of entity literals to Python methods (which our approach cannot handle), in addition to being explicitly declared in a text file (supported by our approach). We can see that the latter option is hardly ever used. As for Dialogflow chatbots, their average LPE value is just over 22, though a remarkable case is the Dining-Out chatbot with more than 1000 literals per entity. This chatbot recommends bars and restaurants, so its entities define long lists of cocktails, food types, and specific bars and restaurants. The next subsection discusses this and other chatbot platform differences in more detail.

7.3.6 Metric distribution across technologies. Our approach enables the measurement of chatbots built with different technologies. To assess whether a given metric has the same probability distribution of values in Dialogflow and Rasa, we applied the Mann-Whitney U (MW) and Kolmogorov-Smirnov (KS) equality tests on the metric values obtained for each technology. The last two columns of Table 6 report the p-values returned by these two statistical tests. A p-value >0.05 in either of the two columns indicates that the metric follows the same probability distribution of values in both technologies.

The results show that the Dialogflow and Rasa chatbots in our dataset follow different distributions for all metrics but PATH and VPTP (i.e., these two metrics are the only ones with p-values of either MW or KS above 0.05). For the rest of metrics, we have that:

- Rasa chatbots have more intents (INT) than Dialogflow chatbots, as well as more confusing phrases (CNF), higher percentages of positive and neutral phrases (SNT^+, $SNT^=$), and higher values of TPI, WPTP, WPO, CPO, VPOP, READ, OPRE, FPATH and CL.
- Dialogflow chatbots have more conversation flows (FLOW), phrases with negative tone (SNT^-), parameters per training phrase (PPTP), and actions per flow (FACT), than Rasa chatbots. The data also show that Dialogflow chatbots have more entities (ENT) than Rasa chatbots, but the latter may be due to Conga's limitation in dealing with entities in Python code.

Overall, Rasa chatbots in our dataset are globally bigger (higher INT, cf. Figure 14); were trained with more examples (TPI) but including more confusing phrases (CNF); have less negative phrases (SNT^-); are more verbose (WPO, CPO) leading to higher reading times (READ) but where phrases are easier to read (OPRE); and maintain longer conversations (higher CL, cf. Figure 16) where users can take more paths (FPATH). As discussed in Section 7.3.5, entity metrics are 0 for Rasa chatbots due to the encoding of entity literals in Python methods.

Regarding Dialogflow chatbots, they have more conversation entry points (FLOW); issue a higher percentage of negative phrases (SNT^-); require users to provide more data in utterances (PPTP); and perform more actions per flow (FACT).

Note that, as a sanity check, we used the MW and KS tests to assess that chatbots of a same technology have the same distribution. For this purpose, we randomly split the dataset of each technology in two subsets, and applied the tests on the subsets. In all cases, we obtained p-values greater than 0.05, which implies an underlying distribution of metric values of Dialogflow chatbots, and also of Rasa chatbots.

7.3.7 Answering RQ1 and RQ1.1. With respect to RQ1, as detailed in Sections 7.3.1–7.3.5, our metrics permit comparing chatbot size using INT; conversation style along Moore and Arar's taxonomy [37] using FLOW, PATH, FPATH and CL; chatbot outputs using WPO, CPO, VPOP, OPRE and SNT; expected user inputs using WPTP, VPTP and PPTP; and chatbot vocabulary size using ENT, LPE, SPL and WL. Moreover, since metrics are defined over Conga, they are applicable to different technologies and enable the comparison of heterogeneous chatbots. Regarding RQ1.1, as described in Section 7.3.6, we found that, for our dataset of chatbots, all metrics but PATH and VPTP follow different distributions for Dialogflow and Rasa.

7.4 RQ2: Detection of quality issues

The previous section hints that metrics can reveal chatbot design issues. Now, to answer RQ2 more precisely, we show in Table 7 the outliers of the metrics separated by technology. For each metric, high outliers are values above Q_3+1.5· IQR, and low outliers are values below Q_1-1.5· IQR (with Q_1 and Q_3 the first and third quartiles, and IQR the interquartile range). Since all our metrics have low outliers below 0, we identify instead chatbots with low metric values below $Q_2/3$.

The table columns show the metric type, metric name, median, high outliers (cut-off value Q_3+1.5· IQR, percentage of chatbots with a metric value above the cut-off, and two outlier chatbots), and low metric values (cut-off value $Q_2/3$, percentage of chatbots with a metric value below the cut-off, and two sample chatbots). For each sample chatbot, the table shows its name and the metric value in parentheses.

Next, we analyse the outliers to detect possible problems related to chatbot size, conversation style, outputs, expected inputs, and vocabulary. The process for identifying problems has been as follows. First, one author checked all outlier chatbots for potential problems. Then, another author

Table 7. Metric outliers per technology.

			High outliers			Low values		
Type	**Metric**	**Median**	**Cutoff**	**Chatbot%**	**Sample chatbots (max. 2)**	**Cutoff**	**Chatbot%**	**Sample chatbots (max. 2)**
Dialogflow								
Global	INT	6	26.5	5.1%	iLearn (89), Car (77)	2	7.7%	ChronoGG (1), fulfillent-importer (2)
	ENT	0	7.5	8.5%	MysteryAnimal (37), googleChallenge (34)	0	52.14%	iLearn (0), insurance_Bot (0)
	FLOW	5	20.5	7.7%	iLearn (89), MysteryAnimal (62)	1.66	1.7%	ChronoGG (1), Buddy-G7 (1)
	PATH	5	24	7.68%	Car (117), iLearn (89)	1.66	1.70%	ChronoGG (1), Buddy-G7 (1)
	CNF	3	75	17.09%	Car (1606), iLearn (1599)	1	40.17%	airportagent (0), basic-slotfilling (0)
	SNT^{+}	4	27.5	0.85%	BikeShop (38)	1.33	45.29%	dialogflow-silly-name-maker (0), fulfillment-temperature-converter (0)
	SNT^{-}	17	62.5	2.56%	dialogflow-google-sign-in (100), dialogflow-ssml (100)	5.66	35.04%	defaults-chatfuel (0), defaults-manychat (0)
Intent	TPI	5.56	20.17	6.83%	Dining-Out (94.67), Hotel-Booking (50.67)	1.85	17.94%	hackathon-group-10 (0.33), in-my-seats-jovo (0.33)
	WPTP	2.41	6.59	1.7%	googleChallenge (9.60), Car (6.8)	0.8	5.98%	fulfillment-multi-locale (0.5), hackathon-group-10 (0.67)
	VPTP	0.44	1.56	0.85%	googleChallenge (1.76)	0.14	12.82%	libsample-advanced (0.03), dialogflow-webhook-boilerplate (0.06)
	PPTP	0.33	2.08	5.12%	Dining-Out (8.33), Hotel-Booking (5)	0.11	29.91%	airportagent (0), kejiiban (0)
	WPO	5.79	20.15	3.41%	HHandoffDAgent (23.11), Education_Chatbot (22.89)	1.93	30.76%	Car (0), fulfillment-temperature-converter (1.5)
	CPO	23.56	86.42	6.83%	Education-Chatbot (125.56), googleChallenge (105.16)	7.85	29.91%	Car (0), ChronoGG (0)
	VPOP	1.04	3.42	0.85%	fulfillment-telephony (3.56)	0.35	31.62%	libsample-advanced (0.1), HOTEL-BOOKING-AGENT2 (0.29)
	READ	4	15	5.12%	Education-Chatbot (19), HHandoffDAgent (19)	1.33	31.62%	fulfillment-temperature-converter (1), fulfillment-multi-locale (1)
Entity	LPE	0	12.5	11.11%	Dining-Out (1177.13), ekgsBot (359.86)	0	52.13%	iLearn (0), airportagent (0)
	SPL	0	5.92	1.70%	Formats (7.13), iotairblower (6.83)	0	54.70%	iLearn (0), airportagent (0)
	WL	0	17.95	1.70%	gordobbot (36), ekgsBot (20.61)	0	54.70%	iLearn (0), airportagent (0)
Flow	FACT	2	3.85	2.56%	HOTEL-BOOKING-AGENT2 (8), keijiban (4.71)	0.66	0%	-
	FPATH	1	1	16.23%	Dining-Out (3.5), HR-Bot (2.33)	0.33	0%	-
	CL	1	3.5	4.27%	enoreese (8), Food-Ordering-Chatbot (7)	0.33	0%	-
Rasa								
Global	INT	9	28.12	9.15%	covid-19-chatbot (143), identity-cloning-toolkit (114)	3	2.1%	07_survey_bot (2), 04_feedback_bot (3)
	ENT	0	0	17%	Foodie-Rasa-Chatbot (9), insurance-en (4)	0	83%	covid-19-chatbot (0), identity-cloning-toolkit (0)
	FLOW	3	11.4	10.6%	identity-cloning-toolkit (102), small-talk-rasa-stack (86)	1	16.9%	covid-19-chatbot (1), dong5854 (1)
	PATH	7	26.5	14.78%	finbot-master (207), identity-cloning-toolkit (115)	2.33	7.74%	concertbot (1), formoriginal (1)
	CNF	10	93.12	13.38%	covid-19-chatbot (10532), identity-cloning-toolkit (3461)	3.33	18.30%	04-feedback-bot (0), 07-survey-bot (0)
	SNT^{+}	17	46.87	0.7%	yassinelamarti (58)	5.66	12.67%	09-news-api (0), Ali (0)
	SNT^{-}	6	36.8	1.4%	FAQ-RASA-NLU (51), trackncov19 (44)	2	38.73%	05-event-bot (0), yassinelamarti (0)
Intent	TPI	8.08	29.21	12.67%	aniketbangar (235.17), sokkalingam (214.33)	2.69	12.67%	concertbot (0), Tiara-A-Chatbot (1)
	WPTP	2.83	6.23	0%	-	0.94	1.40%	concertbot (0), Tiara-A-Chatbot (0.88)
	VPTP	0.55	1.44	0%	-	0.18	5.63%	07-survey-bot (0), 09-news-api (0)
	PPTP	0.25	1.30	1.40%	flight-booking (1.6), Foodie-Rasa-Chatbot (1.5)	0.08	40.14%	rasa-faq-bot (0), 02-lead-bot (0)
	WPO	6.63	13.94	7.04%	Tiara-A-Chatbot (87.63), Data-Mining-Chatbot (73.37)	2.21	0%	-
	CPO	28.39	68.56	8.45%	Tiara-A-Chatbot (440.1), Data-Mining-Chatbot (382.9)	9.46	0%	-
	VPOP	1.2	2.16	5.63%	Data-Mining-Chatbot (3.52), FAQ-RASA-NLU (3.33)	0.4	2.11%	Chatbot-Banking (0.17), WeatherBot (0.2)
	READ	5	11.5	7.04%	Tiara-A-Chatbot (75), Data-Mining-Chatbot (62)	1.66	0.70%	concertbot (1)
Flow	FACT	1.1	1.88	10.56%	Data-Mining-Chatbot (3.92), concertbot (3.5)	0.36	0%	-
	FPATH	1.67	5.46	14.78%	dong5854 (57), rasa-workshop-pydata-berlin (37)	0.55	0%	-
	CL	4	1.33	7.74%	aniketbangar (211), covid-19-chatbot (73)	1.33	7.74%	01-smalltalk-bot (1), 07-survey-bot (1)

assessed the chatbots flagged as problematic by the first author. In case of divergence of opinion, the case was discussed in more detail by all authors, and if no consensus was reached, then the problem was dismissed as spurious.

7.4.1 Size. Intents (INT) provide an estimation of the chatbot size. On the low side, 7.7% of Dialogflow chatbots (9 chatbots) have 2 intents or less, while 3 Rasa chatbots have 3 intents or less. This may be an indication of incomplete chatbots, probably built to experiment with the technology (e.g., ChronoGG to experiment with Dialogflow and Firebase, and 07_survey_bot to experiment with Rasa).

On the high side, 5.1% of Dialogflow chatbots have more than 26 intents, and 9.15% of Rasa chatbots have more than 28 intents. The extreme cases reveal complex chatbots and may signal redundant intents. As Section 7.4.4 will show, covid-19-chatbot (143 intents) and identity-cloning-toolkit (114 intents) have many confusing phrases (CNF) suggesting the existence of similar intents that could have been reused.

7.4.2 Conversation. High outliers of metrics FLOW and PATH may reveal chatbots with unusually wide conversation options. Some of these chatbots, like identity-cloning-toolkit (102 flows, 115 paths), small-talk-rasa-stack (86 flows, 92 paths), finbot-master (22 flows, 207 paths) and iLearn (89 flows, 89 paths) are ELIZA-style chatbots [67] or emulate chit-chat conversation with many possible user entry points. In turn, large values of FPATH signal complex conversations with many possible bifurcations. The chatbots dong5854 (FPATH=57) and rasa-workshop-pydata-berlin (FPATH=37), both performing chit-chat conversations, stand out in this metric. Finally, high outliers of CL (conversation length) may uncover accessibility problems and errors in the conversation design. For instance, aniketbangar, a chatbot to find restaurants, has the highest CL value (211) but only a conversation

entry point (FLOW=1). On inspection, we found that the chatbot is erroneous since it concatenates all flows into one, so that when the chatbot answers with the restaurants, the flow continues with a user greeting, starting the search for restaurants again.

On the other side of the spectrum, low values of FLOW, PATH and FPATH may suggest restricted conversation options or incomplete chatbot designs. For example, Buddy-G7 defines 10 intents but only one conversation flow involving the fallback intent, hence missing conversation options that use the other intents. On inspection, we found that the chatbot has an erroneous setup of the intent contexts in Dialogflow.

7.4.3 Outputs. High outliers of metrics VPOP, CPO, WPO and READ may indicate problematic chatbot outputs. For instance, the chatbot fulfillment-telephony has 3.42 verbs per output phrase (VPOP), which is an indicator of complex chatbot responses. It defines outputs like *"I'm sorry I didn't catch that do you want to continue making a reservation or would you prefer to be transferred to the main line?"*, which lacks punctuation marks separating the phrases within the output.

The CPO of Tiara-A-Chatbot is 440 characters. This may cause accessibility and readability problems, as large answers require scrolling in mobile devices, long reading times (1 minute and 15 seconds according to its READ value), and cannot be fully displayed on social networks like Twitter due to their message length constraints. As an example, Figure 17 shows a response of this chatbot deployed on Telegram using a mobile phone, which requires scrolling as the response has more than 30 lines. This is an example of a content-centric chatbot to access a covid-19 FAQ. However, according to Moore and Arar [37], conversation-centric chatbots with short answers and a natural conversation style are usable in more platforms. Another chatbot with the same problem though to a lesser extent is Education-Chatbot (CPO=125.56, READ=19).

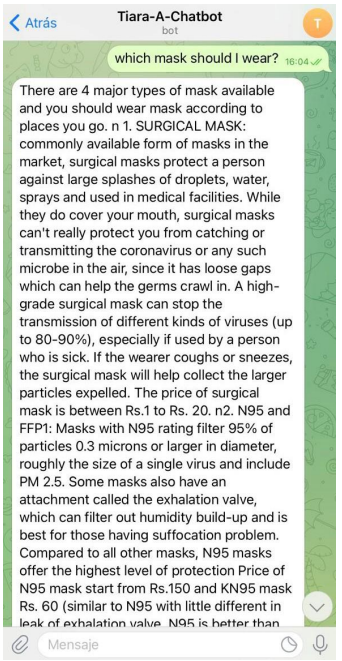


Fig. 17. Long response of Tiara-A-Chatbot in a mobile in Telegram.

The sentiment of the chatbot responses can also affect the user experience. The chatbots dialogflow-google-sign-in, dialogflow-ssml and FAQ-RASA-NLU have 100%, 100% and 51% of negative responses (SNT^-). The responses of FAQ-RASA-NLU are related to covid-19 spread, so many have a negative tone. Chatbots that issue a broad variety of error messages may also have a high percentage of negative responses. For example, dialogflow-ssml only defines 3 responses, but all of them report that the chatbot was not able to access an external service (e.g., *"Sorry, I couldn't get a response for the Welcome intent from your webhook."*). A similar situation occurs with the dialogflow-google-sign-in chatbot. Finally, low values for SNT^+ may be problematic depending on the chatbot domain, like those for chit-chat. Fifteen chatbots (7 Dialogflow chatbots, and 8 Rasa ones) have no responses with positive tone, none of which are chit-chat bots.

7.4.4 Expected inputs. Outliers of metrics concerning expected user utterances (TPI, WPTP, VPTP, PPTP, CNF) may also signal problems.

The chatbots with the fewest training phrases per intent (TPI) are hackathon-group-10 and in-my-seats-jovo. Their average TPI is 0.33, which may affect the chatbot's ability to understand users. Instead, in their analysis of NL engines [1], Abdellatif et al. recommend at least 10 training phrases per intent. Other chatbots, like Tiara-A-Chatbot, define training phrases for a few intents but leave

others empty, signalling an unfinished implementation. In general, incomplete chatbots can be more accurately detected by looking if their minimum value of TPI is zero, than observing their average TPI. With respect to high outliers of TPI, they may be due to the need to recognise complex sentences, but other times they are indicative of an unnecessarily large training set. For example, sokkalingam (TPI=214.33) defines training phrases with many combinations of dates, number of tickets and person names; however, dates and numbers are predefined entities, which makes such an exhaustive training unnecessary. Similarly, aniketbangar (TPI=235.17) has training phrases with many combinations of Indian locations, while defining an entity for those locations would yield a more succinct design.

The length of the training phrases (WPTP) may affect the chatbot understandability. Some chatbots define extraordinarily short training phrases, like fulfillment-multi-locale (0.5), which is a toy example to experiment with multi-language chatbots (English and French). The high outliers of WPTP in the dataset are only for Dialogflow chatbots and do not seem problematic.

High values of PPTP (parameters per training phrase) may point to inputs that are too demanding for the user. An extreme case is Dining-Out, a predefined Dialogflow chatbot for obtaining recommendations to dine out, with 8.33 PPTP. The chatbot demands data like location, dish, beverage, venue type, etc., in many training phrases. This may lead to users having to input long phrases or having to answer many follow-up prompts from the chatbot.

Related to user experience, high outliers of metric CNF may reveal chatbot understanding problems due to the existence of similar training phrases in different intents, which may confuse the chatbots. Overall, 17.09% of Dialogflow chatbots and 13.38% of Rasa chatbots have confusing phrases in different intents, with extreme cases such as covid-19-chatbot (10532), identity-cloning-toolkit (3461), Car (1606) and iLearn (1599). For example, several intents of Car have similar training phrases, such as *"turn down the heater for each seat in the car"* and *"turn off the heating in my car"*. Other chatbots with confusing training phrases are small-talk-rasa-stack (*"I am very bored"* / *"I'm bored of you"*), googleChallenge (*"What is the time duration for completing Masters in Artificial Intelligence?"* / *"Completion period for masters in AI?"*), Dining-Out (*"now cafe"* / *"find cafe"*), and BikeShop (*"Can you fix my road bike?"* / *"Can you service my bike?"*). High values of CNF are more frequent in chatbots with many intents, as this increases the probability of having similar intents. Sometimes, high CNF values stem from an incorrect interpretation of what training entails. For example, covid-19-chatbot sometimes uses tags (e.g., coronavirus, covid, corona) instead of full-fledged phrases, which may hamper correct intent recognition since these tags overlap in many intents. This way, CNF helps detecting intents that a chatbot may mismatch, without resorting to intensive dynamic testing. High CNF values can also be an indicator that some intents could be merged. For example, chatbot covid-19-chatbot has several intents to express that the user has tested positive in covid, and these intents could be merged.

7.4.5 Vocabulary. Entity metrics provide insights on the chatbot vocabulary and may uncover problems in it.

In Table 7, the median and low cut-off value of metrics LPE, SPL and WL is zero in Dialogflow. This is because more than a half of the Dialogflow chatbots lack entities, which can be considered normal. However, chatbots that define entities (ENT>0) but have few literals per entity (LPE) indicate poorly defined entities. This is the case of the Dialogflow chatbot your_song, which defines entities with just one literal, e.g., for music genres, which may compromise a correct entity recognition. In other cases, chatbots may have entities but LPE is zero because the entities are defined via regular expressions or functions. This is the case for the 17 Rasa chatbots defining entities in the dataset.

In addition, WL helps detecting unusually long entity literals. As an example, the Dialogflow chatbot gordobbot defines entities for food origins or cooking utensils, and its WL value is 36.

Inspecting the definition of these entities reveals a misconception on the use of entity literals, as instead of providing synonyms for literals, the definition provides explanatory phrases.

7.4.6 Answering RQ2. To answer RQ2, we have manually checked all chatbots with low or high metric outliers to assess if they have problems. Table 8 summarises the results. For each metric, columns 4 to 7 show the number of problematic Dialogflow and Rasa chatbots, and the percentage they represent in the set of outliers for the metric. The last two columns describe the problem found and its type. Detailed information on the discovered problems are available at https://github.com/ASYM0B/MetricsOutliers. Overall, we detected 16 types of problems implying design errors, usability problems, or poor designs that could be improved by re-designs. We refrain from reporting usability problems that require a subjective evaluation, like chatbot responses with a negative tone, or possibly confusing phrases between intents, like *"I am very bored"* / *"I'm bored of you"* in chatbot small-talkrasa-stack, or "*What is the time duration for completing Masters in Artificial Intelligence?*" / "*Completion period for masters in AI?*" in chatbot googleChallenge.

Table 8. Summary of problems detected in chatbots with high metric outliers or low metric values. Legend: n/a indicates an empty set of outliers; * indicates the percentage is taken on the whole dataset of chatbots.

Aspect	Metric	Value	# Problems, Outlier%				Problem description	Problem type
			Dialogflow		Rasa			
Size	INT	low	9	100%	3	100%	Incomplete/Toy chatbot	Incomplete design, Usability
		high	2	33.4%	5	55.6%	Redundant intents (when CNF high)	Re-design
Conversation	FLOW	low	2	100%	5	20.9%	Incomplete/Toy chatbot	Incomplete design, Usability
		high	0	0%	7	46.7%	Repeated or redundant flows	Design error, Re-design
	PATH	low	2	100%	6	54.6%	Incomplete/Toy chatbot	Incomplete design, Usability
		high	0	0%	16	76.2%	Repeated or redundant paths	Design error, Re-design
	FPATH	low	n/a	n/a	n/a	n/a	Incomplete/Toy chatbot	Incomplete design, Usability
		high	1	5.3%	15	71.5%	Repeated or redundant paths	Design error, Re-design
	CL	high	0	0%	1	9.1%	Long conversation (hard to complete)	Usability
		high	0	0%	9	81.9%	Error in conversation design	Design error
Outputs	VPOP	high	1	100%	2	25%	Missing punctuation signs	Usability
	CPO	high	0	0%	4	33.4%	Long responses (>280 chars)	Usability, Deployability
	WPO	high	0	0%	5	50%	Long responses (>50 words)	Usability, Comprehensibility
	READ	high	0	0%	5	50%	Long reading times (>30 secs)	Usability, Efficiency
Inputs	TPI	low	11	52.4%	4	100%	Intents poorly trained (≤4 phrases)	Usability
			13	11.2%*	45	31.7%*	Intents without training phrases	Incomplete design, Re-design
		high	2	25%	14	77.8%	Repeated or redundant phrases	Re-design
	WPTP	low	7	100%	2	100%	Bad quality of training set	Usability, Incomplete design
	CNF	high	7	35%	5	27.8%	Confusing intents	Usability
Vocabulary	LPE	low	3	100%	n/a	n/a	Ill-defined entities (when ENT>0)	Usability
	WL	high	1	50%	n/a	n/a	Bad use of entity literals	Design error

As the table shows, low values for INT, FLOW and PATH typically revealed incomplete or toy chatbots. Conversely, high INT values, in combination with high CNF values, uncovered redundant intents. Some chatbots with extremely high values for FLOW, PATH and FPATH had repeated or redundant flows or paths that could be deleted or simplified to improve the design quality. Inspecting chatbots with high CL values uncovered design errors (concatenated conversation flows) or conversations unlikely to occur in practice (e.g., a chit-chat chatbot that expects the user to jump over unrelated topics in long conversation flows).

Regarding chatbot outputs, some high VPOP values were due to missing punctuation signs, while large values of CPO, WPO and READ can cause usability problems (inability to deploy the chatbot in certain channels, or sentences that are long or difficult to understand). The table shows the problematic chatbots taking thresholds of 280 characters (Twitter's maximum message size), 50 words and 30 seconds. Still, other thresholds can be used depending on the target channel, chatbot domain and audience [37].

Regarding chatbot inputs, low values of TPI revealed some poorly trained intents, which either could be removed or were indicative of incomplete designs. We set the bar on 4 training phrases (a bare minimum which makes tools like Dialogflow complain) but other thresholds are possible (e.g., 10 as Abdellatif et al. recommend [1]). The table also shows the chatbots with empty intents (i.e., the minimum value of TPI is zero for any of the chatbot intents). Other problems discovered when checking metric outliers were the presence of redundant phrases which only varied in their parameter values (high TPI), low-quality training phrases made of one or two words (low WPTP), and overlapping intents with many similar training phrases (high CNF).

Finally, the vocabulary metrics only apply to Dialogflow. They helped uncovering under-defined entities (low LPE) and erroneous literals (high WL).

Overall, from the set of chatbots in the dataset with metric outliers, the percentage of those with problems range from 5.3% to 100% depending on the metric and technology (more than 50% in average). Still, to assess the effectiveness of inspecting outliers to find problems, we need to analyse the prevalence of such problems in the population of chatbots without metric outliers. Table 9 shows the result of this analysis. The percentage of problematic chatbots without metric outliers is generally much lower than the percentage of problematic chatbots with metric outliers. Among non-outliers, the percentage of chatbots with problems range from 0% to 39.2% depending on the metric and technology, though it is typically below 4%. Dialogflow has a few spurious cases where this percentage is slightly higher for non-outliers: 1 chatbot with redundant paths, 1 with long conversations, and 3 with errors in the conversation design (compared to 0 in the outliers set). However, the metric outliers catched the most problematic chatbots. In Dialogflow, we found 61 problems among the outliers (18 among non-outliers), and in Rasa, we found 153 problems among the outliers (106 among non-outliers).

Table 9. Summary of problems detected in chatbots with no high metric outliers or low metric values.

Aspect	Metric	Value	# Problems, Non-outlier%				Problem description
			Dialogflow		Rasa		
Size	INT	low	0	0%	1	0.8%	Incomplete/Toy chatbot
		high	0	0%	0	0%	Redundant intents (when CNF high)
Conversation	FLOW	low	0	0%	1	0.9%	Incomplete/Toy chatbot
		high	0	0%	1	0.8%	Repeated or redundant flows
	PATH	low	0	0%	1	0.8%	Incomplete/Toy chatbot
		high	1	1%	4	3.4%	Repeated or redundant paths
	FPATH	low	0	0%	1	0.8%	Incomplete/Toy chatbot
		high	0	0%	4	3.4%	Repeated or redundant paths
	CL	high	1	0.9%	5	3.9%	Long conversation (hard to complete)
		high	3	2.7%	5	3.9%	Error in conversation design
Outputs	VPOP	high	0	0%	0	0%	Missing punctuation signs
	CPO	high	0	0%	2	1.6%	Long responses (>280 chars)
	WPO	high	0	0%	2	1.6%	Long responses (>50 words)
	READ	high	0	0%	2	1.6%	Long reading times (>30 secs)
Inputs	TPI	low	11	11.5%	54	39.2%	Intents poorly trained (≤4 phrases)
		high	2	1.9%	21	17%	Repeated or redundant phrases
	WPTP	low	0	0%	2	1.5%	Bad quality of training set
	CNF	high	0	0%	0	0%	Confusing intents
Vocabulary	LPE	low	0	0%	0	0%	Ill-defined entities (when ENT>0)
	WL	high	0	0%	0	0%	Bad use of entity literals

In conclusion, we can answer RQ2 positively, since a substantial amount of chatbots with outliers in their metric values presented problems. Focussing on analysing outliers is effective since, in our dataset, most considered problems occurred among the outlier chatbots. Moreover, the most common problem among non-outlier chatbots – intents poorly trained, with less than 5 phrases – can be easily caught with metrics.

7.5 RQ3: Chatbot clustering

To answer this research question, we performed a similar experiment to the one by Basciani and collaborators [4], which was directed to evaluate a clustering method for meta-models.

First, one voluntary manually labelled the 259 chatbots in the dataset with their domain, such as "hotels", "basic conversations" or "food". Each chatbot could be assigned several labels (e.g., a chatbot for searching restaurants could be labelled with both "search" and "restaurant"). This manual labelling yielded 43 clusters, 6 of them with a single chatbot (so-called singleton clusters). Table 10 characterises the manual clusters, which have sizes ranging from 1 to 32 chatbots, with an average size of 7.7 and median 5. Further details of the clusters are available at https://github.com/ASYM0B/SemanticClusteringEvaluation.

Table 10. Comparison of manual clustering and best vocabulary-based clustering.

	Manual clustering	**Voc.-based clustering**
#Clusters	43	29
Max labels per chatbot	3	1
#Singleton clusters	6	3
Size of smallest cluster	1	1
Size of largest cluster	32	43
Average cluster size	7.7	9.2
Median cluster size	5	15

Next, we applied our automated vocabulary-based clustering to the same chatbots. As explained in Section 5.2 (step 6), our clustering algorithm works by iteratively combining the "closest" pair of chatbot clusters into a single cluster. For this purpose, it can use different methods, called *linkage methods*, to calculate the distance between two clusters. For instance, in single-linkage, the distance between two clusters is equal to the distance of the pair of elements (one in each cluster) that are closest to each other, while in complete-linkage, it is the distance of the pair of elements that are farthest away (see [55] for a description of other linkage methods). In the experiment, we used different linkage methods and distance thresholds (from 0.01 to 0.99 with 0.01 increments) to form the clusters. Then, for each combination of linkage method and distance threshold, we computed the balanced accuracy of the returned clusters as we explain below. Table 10 summarises the vocabulary-based clustering with the best balanced accuracy (0.664). It yields 29 clusters containing between 1 and 43 chatbots (9.2 chatbots in average, median of 15, and 3 singleton clusters). An inspection of the clusters shows that they group chatbots about hotels, insurance and banking, news, restaurants, food ordering, time zones, shopping, education, health, songs, and weather, among others.

In the following, we explain our method to identify the vocabulary-based clustering configuration with the most accurate result. Specifically, we used the metric *balanced accuracy* to quantify the percentage of chatbot pairs correctly sharing or not a cluster, taking the manual clusters as the ground truth. For this purpose, given a set of (manually or automatically) clustered chatbots $C = \{c_1, ..., c_n\}$, we built its clustering matrix M_C as follows:

- $M_{Cij} = 1$ if c_i and c_j belong to a same cluster
- $M_{Cij} = 0$ otherwise

Then, we compared the manual clustering matrix M with each vocabulary-based clustering matrix V[21], counting how many chatbot pairs (c_i, c_j) belonged to one of four possible sets:

- Correctly grouped: $CG = |\{(c_i, c_j) \mid V_{ij} = M_{ij} = 1\}|$ is the number of *true positives*.
- Correctly separated: $CS = |\{(c_i, c_j) \mid V_{ij} = M_{ij} = 0\}|$ is the number of *true negatives*.
- Incorrectly grouped: $IG = |\{(c_i, c_j) \mid V_{ij} = 1 \wedge M_{ij} = 0\}|$ is the number of *false positives*.
- Incorrectly separated: $IS = |\{(c_i, c_j) \mid V_{ij} = 0 \wedge M_{ij} = 1\}|$ is the number of *false negatives*.

Next, we calculated balanced accuracy as:

$$BA = \frac{1}{2} \cdot \left(\frac{CS}{CS + IG} + \frac{CG}{CG + IS} \right)$$

The second term of the formula ($\frac{CG}{CG+IS}$) is the percentage of correct 1's returned by the clustering. The first term ($\frac{CS}{CS+IG}$) is the percentage of correct 0's returned by the clustering. For non-overlapping clusters, BA is just normal recall, because a 100% recall of 1's implies a 100% recall of 0's, and vice versa. However, for overlapping clusters, a 100% recall of 0's does not imply a 100% recall of 1's. This is why we balance both terms in the formula for BA.

We use balanced accuracy to quantify the accuracy of our clustering approach because the matrices M and V are sparse (i.e., unbalanced): M has 94% of 0's, and the most accurate V has 93% of 0's. Instead, using precision would give more importance to guessing 0's than to guessing 1's. For example, a V matrix that only contains 0's would obtain a precision close to 1, which does not fit our purposes. The formula BA eliminates this bias.

Figure 18 depicts the value of BA for each linkage method and distance threshold. As a summary, Table 11 shows the distance threshold that permits obtaining the highest balanced accuracy for each linkage method. The best accuracy (0.664) was achieved using weighted linkage and a threshold of 0.97. Even though all linkage methods achieved similar accuracy, the weighted and average methods performed slightly better than the rest. For this reason, our tool uses the weighted linkage method.

Table 11. Best balanced accuracy for each linkage method.

Linkage method	Distance threshold	Best bal. accuracy
Single	0.71	0.615
Complete	0.97	0.619
Average	0.96	0.641
Centroid	0.67	0.607
Weighted	0.97	**0.664**
Median	0.73	0.622

Finally, we have compared our clustering approach with four baselines: a clustering matrix containing only 0's, another containing only 1's, a third one with binary values randomly generated, and our previous bag-of-words method [33]. The balanced accuracy of the first two cases is 0.5, the one of the third case is 0.502, and the fourth is 0.4. In comparison, the balanced accuracy of our clustering approach was 0.664, which is a significant increase w.r.t. the baselines, and shows the benefits of using TF-IDF over bag-of-words.

[21] The vocabulary-based clustering matrices V represent a reflexive, symmetric, transitive relation between chatbots, since the clusters are disjoint. Instead, the manual clustering matrix M may not be transitive, since we allowed chatbots with several manual labels. This means that our vocabulary-based clustering will not be able to produce the clusters of the manual matrix, if the manual clusters are not disjoint.

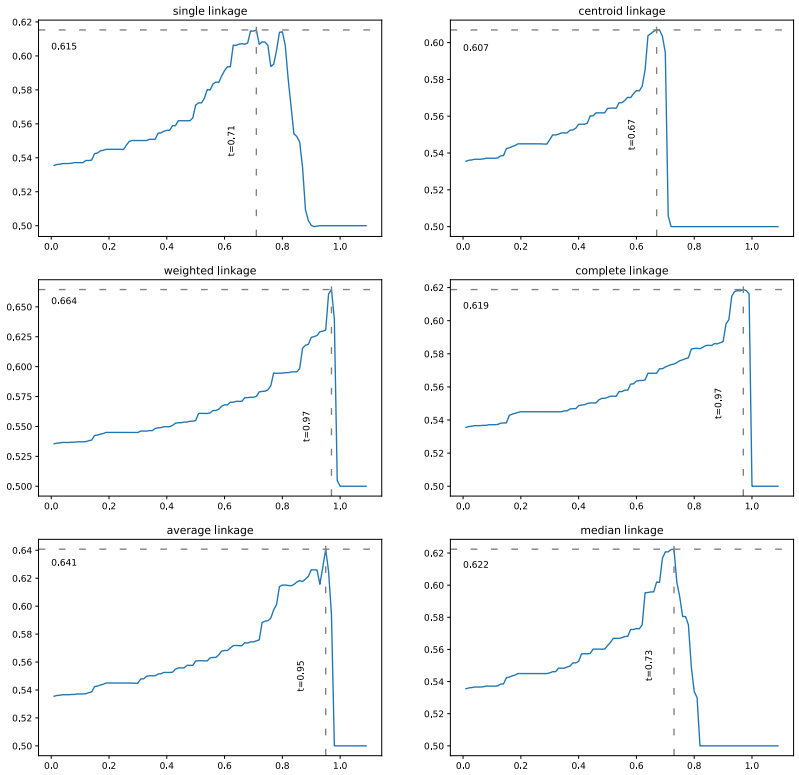


Fig. 18. Balanced accuracy of vocabulary-based clustering depending on the selected linkage method and distance threshold.

7.5.1 Answering RQ3. Overall, we can answer *RQ3* positively: vocabulary-based clustering can create meaningful groups of semantically related chatbots (e.g., groups of chatbots about hotels, restaurants, or weather, among others). To have a quantitative assessment, we measured the fraction of correctly clustered chatbot pairs using balanced accuracy, and compared against four baselines obtaining a substantially higher balanced accuracy (0.664 vs 0.502).

7.6 Threats to validity

Next, we discuss threats to the internal and external validity of our evaluation. Internal validity is the extent to which the findings of an experiment truly represent a cause-and-effect relationship. External validity is concerned with the extent to which the results of a study can be generalised.

7.6.1 Internal validity. Regarding RQ1, a limitation of our evaluation is the use of custom-made importers from existing platforms into Conga. In particular, Rasa permits programming some aspects of chatbots in several ways. For example, one may train a chatbot on the fly instead of using training phrases, or change the conversation flow using Python. Our importer does not handle such code-based functionality variants, which may affect the metric values.

Regarding RQ2, we detected evident problems in some chatbots using metrics. However, we did not confirm those problems with the chatbot authors. Even if this would be desirable, according to their profile, the authors are frequently hobbyist programmers or students, which may hamper confirming the problems. We did not perform any cleaning (e.g., of small chatbots) in the dataset,

utilizing all chatbots we found. As a consequence, the dataset may contain unfinished chatbots. This is intentional since we argue that metrics can serve for quality assurance during chatbot development, and so, we want our metrics to detect problems related to incomplete designs.

With regards to RQ3, one author of the paper labelled the chatbots manually. To avoid any bias, this labelling was performed before the execution of the vocabulary-based clustering. Even if a labelling process involving more than one person may be somewhat different, our labelling reflects the expectations of a potential user for which our clustering method provided a reasonable grouping. A labelling made by several people also has the risk of using dissimilar criteria for labelling. Actually, a challenge for the community is the proposal of tools helping the manual labelling of chatbot datasets, in the style of [32].

7.6.2 External validity. We mitigate external threats by defining our metrics and clustering methods on a neutral notation (Conga) which has been designed out of 15 well-known chatbot development platforms, and using a dataset of third-party chatbots. While the use of Conga increases our confidence on the applicability of our proposal to the most common chatbot development platforms, we cannot claim generality as there may be other platforms supporting specific chatbot features or idioms not captured by Conga.

Regarding RQ1, the limited size of the dataset does not allow claiming differences or similarities between the technology or source of the chatbots, for which we would need a larger scale experiment. Instead, our goal was to hint at the convenience of the proposed static chatbot metrics.

Related to RQ2, while metrics can detect problems in chatbots, problems need to be confirmed by inspection. Not all possible chatbot problems can be detected by metrics, for which a combination of static analysis and testing would be desirable. In addition, the results in Table 8 show a higher number of problems in Rasa chatbots than in Dialogflow chatbots. However, these problems cannot be directly attributed to the usage of a particular technology, for which a wider study would be needed. Finally, RQ2 has assessed the effectiveness of metrics but not their usefulness or value for chatbot developers. The latter would require conducting a user study asking chatbots developers to identify possible issues with and without the metrics. Such a study is left for future work.

As for RQ3, we show that our vocabulary-based clustering has better accuracy than four baseline methods. This experiment considers 259 third-party chatbots to avoid any bias and promote generality. However, using a different set of chatbots may result in a different accuracy value.

7.7 Discussion of findings

We conclude this section by a qualitative discussion of the results, outlining actionable insights for chatbot researchers, tool builders, and practitioners.

Investigation on conversation design (researchers, practitioners). Sections 7.3 and 7.4 showed that our metrics can help gaining valuable knowledge from chatbot repositories. In particular, metrics can be used to detect common conversation design patterns, or deviations from good conversational practices. As an example, if we take Moore and Arar's classification of conversation styles [37], we identify that 46% of the chatbots in our dataset have linear conversations, most of them just one-turn (being *system-centric*), and just two chatbots output large amounts of information on a topic (being *content-centric*).

Choosing a chatbot development tool (tool builders, practitioners). Our metrics enable comparing chatbots built with heterogeneous technologies. For the dataset considered in our experiments, Section 7.3 revealed differences on the metric values depending on the chatbot technology. In our dataset, Rasa chatbots have more intents, confusing phrases, and training phrases per intent; whereas Dialogflow chatbots have more conversation flows, phrases with negative tone, and parameters. It would be interesting to investigate whether, in general, these

differences could be attributed to the technology used, as well as to identify what features can make chatbot development tools less prone to user errors. For example, Rasa specifications consist of text files, which eases the creation of variations of training phrases (higher TPI), but where copy-and-paste actions may result in duplicated training phrases (higher CNF). Instead, training phrases in Dialogflow are introduced by means of forms, and include facilities to define phrase parameters (higher PPTP). In the future, our findings, based on metrics, should be complemented with user studies to find causes for these differences within tools.

Integrated quality assurance (tool builders, practitioners). Section 7.4 has demonstrated that some quality issues can be detected statically, at design time. For this reason, we foresee the integration of metrics within chatbot tools, e.g., to detect low number of training phrases, repeated phrases, long responses, or confusing phrases. Alternatively, practitioners could make use of our metrics to gain insights of their designs. For this matter, we are currently working on deploying the calculation of metrics as a Github action[22], which can be easily integrated into custom software development workflows.

Chatbot reuse (tool builders, practitioners). Both Dialogflow and Rasa provide predefined chatbot templates for different domains, which users can complete and adapt to their needs. In addition to this kind of planned reuse, we also advocate for enabling the unanticipated reuse of existing chatbots. Chatbot clustering, as presented in this paper, is a first step towards this goal. As Section 7.5 showed, our clustering mechanism is able to create meaningful groups of related chatbots by conversation topic. In the future, several improvements could be developed atop our clustering proposal to achieve a better reuse mechanism, such as a facility to find *sets* of chatbots by topic – so that developers may choose the most appropriate starting point for their chatbot – and automated support to adapt existing chatbots to the reuser needs.

On chatbots based on Large Language Models (tool builders). The advances in Large Language Models (LLMs) [70] has prompted the appearance of open-domain chatbots like ChatGPT or Bard. Those LLMs have been trained on enormous amounts of data, and use generative technologies to synthesise outputs from given user *prompts*. However, building a reliable LLM-based chatbot using prompts alone is challenging [69]. To facilitate this task, a natural move for chatbot tool vendors may be to integrate LLM technology into task-oriented chatbot construction tools[23]. This will trigger the need to migrate existing intent-based chatbots into LLM-based chatbots. We argue that a neutral chatbot design language would be helpful for this task. While chatbots defined with Conga are currently based on intents, we are working on its expansion to consider chatbots based on prompts, which will enable an automated migration.

8 CONCLUSION AND FUTURE WORK

Chatbots are increasingly relevant nowadays, so techniques for assessing, comparing and clustering chatbots before their deployment are required. To this aim, we have proposed a suite of metrics and two clustering mechanisms applicable over heterogeneous chatbot designs independently of their implementation technology. Our proposal is supported by the tool Asymob, which can be used both as a web platform and via its REST API for integration within specific chatbot platforms or development processes. We have evaluated the approach on a dataset of 259 chatbots, demonstrating the usefulness of the metrics – for chatbot quality assurance and detecting problems – and the clustering.

In the future, we would like to study how developers perceive and value our metrics by conducting qualitative studies, such as surveys. We also plan to study correlations between our metrics, with other development metrics like effort, and with usability metrics collected dynamically. The latter

[22] https://docs.github.com/en/actions [23] An improvement that has been already announced for Rasa.

would allow us to assess empirically the influence of our internal design metrics to external quality factors related to effectiveness, efficiency and satisfaction. Ultimately, we would like to derive metric thresholds to guide developers during chatbot construction. On a more general setting, we would like to investigate the definition of custom quality models for assessing the quality of chatbots, including both internal metrics and quality in-use metrics (e.g., in the style of [54]). We would like to conduct larger-scale studies to better understand the type of errors in chatbots, and their links to the technologies used. For this, we plan to use a combination of metrics and static design analysis. We are also interested in supporting other chatbot representations for semantic clustering. These may include the use of embeddings like Word2Vec or pre-trained language models like BERT [13]. At the tool level, we are working on presenting warnings about outliers, and on a graphical editor to inspect chatbot designs. Finally, finding chatbots is cumbersome with current search engines. For this reason, we would like to propose a dedicated crawler and search engine for chatbots, able to accurately find chatbot projects for a given technology.

DATA AND CODE AVAILABILITY

The data and code that support the findings of this paper are openly available at:

- Deployed Asymob service: http://miso.ii.uam.es/asymobService
- Asymob core code: https://github.com/PabloCCanizares/asymob
- Datasets and experiment results: https://github.com/asym0b

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