Journal of Computer Science Research
https://journals.bilpubgroup.com/index.php/jcsr

ARTICLE

Inquiring Natural Language Processing Capabilities on Robotic Systems through Virtual Assistants: A Systemic Approach

Ioannis Giachos[1], *Evangelos C. Papakitsos*[1*], *Petros Savvidis*[1,2], *Nikolaos Laskaris*[1]

[1] *Department of Industrial Design & Production Engineering, University of West Attica, Egaleo, Athens, 12241, Greece*
[2] *Research Laboratory of Electronic Automation, Telematics and Cyber-Physical Systems, University of West Attica, Egaleo, Athens, 12241, Greece*

ABSTRACT

This paper attempts to approach the interface of a robot from the perspective of virtual assistants. Virtual assistants can also be characterized as the mind of a robot, since they manage communication and action with the rest of the world they exist in. Therefore, virtual assistants can also be described as the brain of a robot and they include a Natural Language Processing (NLP) module for conducting communication in their human-robot interface. This work is focused on inquiring and enhancing the capabilities of this module. The problem is that nothing much is revealed about the nature of the human-robot interface of commercial virtual assistants. Therefore, any new attempt of developing such a capability has to start from scratch. Accordingly, to include corresponding capabilities to a developing NLP system of a virtual assistant, a method of systemic semantic modelling is proposed and applied. For this purpose, the paper briefly reviews the evolution of virtual assistants from the first assistant, in the form of a game, to the latest assistant that has significantly elevated their standards. Then there is a reference to the evolution of their services and their continued offerings, as well as future expectations. The paper presents their structure and the technologies used, according to the data provided by the development companies to the public, while an attempt is made to classify virtual assistants, based on their characteristics and capabilities. Consequently, a robotic NLP interface is being developed, based on the communicative power of a proposed systemic conceptual model that may enhance the NLP capabilities of virtual assistants, being tested through a small natural language dictionary in Greek.

Keywords: Natural language processing; Robotic systems; Virtual assistant; Human-robot interface

*CORRESPONDING AUTHOR:
Evangelos C. Papakitsos, Department of Industrial Design & Production Engineering, University of West Attica, Egaleo, Athens, 12241, Greece; Email: papakitsev@uniwa.gr

ARTICLE INFO
Received: 9 March 2023 | Revised: 4 April 2023 | Accepted: 7 April 2023 | Published Online: 18 April 2023
DOI: https://doi.org/10.30564/jcsr.v5i2.5537

CITATION
Giachos, I., Papakitsos, E.C., Savvidis, P., et al., 2023. Inquiring Natural Language Processing Capabilities on Robotic Systems through Virtual Assistants: A Systemic Approach. Journal of Computer Science Research. 5(2): 28-36. DOI: https://doi.org/10.30564/jcsr.v5i2.5537

1. Introduction

One of the most important parts of an advanced humanoid robot is the communication function. More specifically, the way that it receives orders from a person, or an interlocutor, as well as the means by which it returns information to him/her. The Human-Robot Interface (HRI) of an advanced humanoid robot consists of a unit to collect the natural language input, a unit to process the received sentences and a unit for the semantic representation of these sentences [1]. This is exactly what the robotic system needs to be able to process for understanding commands in natural language. So, there is a Natural Language Processing (NLP) unit that aims to analyze incoming sentences/commands and a Natural Language Understanding (NLU) unit for understanding these sentences. The recognized request is forwarded to subsequent units to begin the response process. This part of the machine that is described above is found autonomously in many applications for many years, such as an Intelligent Virtual Assistant (IVA) or Intelligent Personal Assistant (IPA). The subtle difference between them is that an IVA is an artificial intelligence (AI) software that can provide interactive and personalized services to users through voice and text-based interactions. It is designed to assist users in performing tasks, answering questions, providing recommendations, and facilitating transactions. An IVA can be integrated into various devices and applications, such as smart phones, smart home devices, chat-bots, and customer service platforms. On the other hand, an IPA is a type of virtual assistant that is designed to provide personalized assistance to individual users, based on their preferences, habits, and history. It can be integrated into various devices, such as smart phones, smart watches, and smart speakers, to help users perform tasks, manage information, and control their environments by using voice or text commands.

The first system known that responded to a voice command was a commercial children's toy produced in 1922 by Elmwood Button Co [2], "Radio Rex". It was a toy dog and was responding to its name called. In fact, the toy's system was designed to be triggered when the vowel in "Rex" was sounded. A more complicated system that could be considered as an ancestor of IVA systems was a device called "Voder", which was developed by the Bell Telephone Laboratories in 1939 [3,4]. Voder was not a virtual assistant in the modern sense, but rather a machine that could synthesize human speech. It was one of the earliest examples of a speech synthesizer and was demonstrated at the 1939 World's Fair in New York. Voder consisted of a console with a keyboard and foot pedals, which were used to produce speech sounds by manipulating various controls. An operator could type out a message on the keyboard, and Voder would produce a synthetic speech output based on the input. While Voder was not an intelligent machine, like modern virtual assistants, it was a significant step forward, in the development of speech technology and paved the way for the future advanced speech synthesis and recognition systems. It's worth noting that there were also earlier attempts at speech synthesis, such as the "talking machines", invented in the late 1800s [5,6], but these were not electronic devices like Voder.

In the following decades, there were several recorded efforts, but also important steps towards evolution. The birth decade of virtual assistants was the 90s. The first virtual assistant, known as "Dr. Sbaitso", was released by Creative Labs in 1991 [7,8]. However, the term "virtual assistant" did not come into widespread use until the mid-2000s, with the introduction of Apple's Siri in 2011 and other similar voice assistants. Since then, there have been many virtual assistants, developed for various devices and platforms.

So, while the concept of a virtual assistant has been around since the early 1990s, the specific term "virtual assistant" refers to more recent developments in the field of AI and speech recognition. Nevertheless, nothing much is revealed about the nature of the human-robot interface of commercial IVAs, therefore, any new attempt of developing such a capability has to start from scratch. Accordingly, to include corresponding capabilities to a developing NLP system of a virtual assistant, a methodology of inquiring and development is required.

2. Methodology

Initially, in order to manage the necessary information on the NLP capabilities of an IVA, the systemic methodology in information management through the Organizational Method for Analyzing Systems technique (OMAS-III) [9] was utilized in this inquiry. The following subsections present the analysis and application of this methodology for the selection of literature references.

2.1 Systemic information management

Information management is the most critical activity of any research work. The concepts of systemic information management are shown in **Table 1** and discussed below.

The information cycle includes the collection of primary data ("input"), its processing and finally its dissemination ("output"). In each of these three phases, information is stored as a necessary activity of any information system. The three phases follow the General Systems Model (GSM) [10], since the collection phase corresponds to the input of the information system, while the dissemination phase corresponds to its output. Moreover, each phase has its own particular features.

The primary data are collected from their sources, which can be divided into primary, secondary and tertiary sources (see also Section 2.2, with regard to literature sources). The typology of the data refers to the form of their origin and is divided into oral, printed, electronic/digital and audiovisual (in the respective analogue media). The processing of data involves, in order, their evaluation, their structuring into categories (classification) and their correlation, both with each other and with other pre-existing data. This is followed by information generation, where conclusions (secondary information) are drawn from the primary data. Finally, information dissemination is carried out by the same means as in the typology of data collection. Data evaluation is discussed in more detail in the next section.

2.2 Systemic information assessment

Useful information should be valid, timely, specific, clear and complete (**Table 1**). Validity is investigated in terms of sources and requires cross-checking when there is a multiplicity of sources. It is assessed for its reliability and accuracy. Reliability increases, the more the data are collected from primary sources, their subject matter is known, the method of collection and the purpose of their display, as well. The timeliness of the information refers both to its short distance in time from the events under consideration (Recent) and to its collection at the time it is needed (Prompt). The relevant assessment questions are:

- How recent the data are?
- Are data out of date?
- Information specificity is about sorting out relevant information from irrelevant ("noise"). In research methodology, it also appears in the properties of Relevance and Significance [12]. In terms of relevance, the followings are considered:
- Are the research questions/objectives relevant to ours and therefore relevant to our research?
- Is the research context different and far removed from our research questions and objectives?
- Are there references to this item or its author in other useful data?
- Does the item support or contradict our arguments? (Both are useful.)

In terms of relevance, the following are considered:

- Do the data appear to be biased? Do they use irrational arguments, emotionally charged words, or do they only choose cases that support the conclusion drawn? Even so, it may be relevant to our critical review.
- Are there any methodological omissions in the work (e.g., sample selection, data collection, data analysis)? Even if there are, this may be relevant to our project.
- Is the accuracy sufficient? Even if it is not, it may be the only relevant evidence that can be found.

Table 1. Systemic information management [11].

<table>
<tr><td rowspan="7">Collection (Input)</td><td rowspan="3">Sources</td><td>Primary</td><td colspan="2" rowspan="3">Cross-checking</td></tr>
<tr><td>Secondary</td></tr>
<tr><td>Tertiary</td></tr>
<tr><td rowspan="4">Typology</td><td>Oral</td><td colspan="2" rowspan="4"></td></tr>
<tr><td>Printed</td></tr>
<tr><td>Digital</td></tr>
<tr><td>Audio-visual</td></tr>
<tr><td rowspan="10">Processing</td><td rowspan="7">Evaluation</td><td rowspan="2">Valid</td><td>Credible</td><td rowspan="2">Cross-checking</td></tr>
<tr><td>Precise</td></tr>
<tr><td rowspan="2">Timely</td><td>Prompt</td><td rowspan="2"></td></tr>
<tr><td>Recent</td></tr>
<tr><td>Relevant</td><td colspan="2" rowspan="5"></td></tr>
<tr><td>Clear</td></tr>
<tr><td>Complete</td></tr>
<tr><td rowspan="2">Structuring</td><td>Classification</td></tr>
<tr><td>Correlation</td></tr>
<tr><td>Creation</td><td colspan="3">From Primary to Secondary</td></tr>
<tr><td>Dissemination</td><td colspan="4">(Output)</td></tr>
</table>

- Does the data provide suggestions for future research?

The clarity of the information is assessed in terms of the comprehensibility of the wording, while completeness can be tested in terms of communicative adequacy. This is where Systems Methodology makes a decisive contribution, by using the OMAS-III as a tool for assessing the completeness of information, by checking the following (through answering the "journalists' questions", shown below enclosed in parentheses):

- The purpose served ("Why?").
- The results/conclusions described ("Output/What?").
- The quantitative factors (means/resources) needed ("Input/How much?").
- The rules/conditions governing the research context ("How?").
- The human factor traits involved ("Who?").
- The characteristics of the location of the subject under investigation ("Where?").
- The temporal elements of the subject under consideration ("When?").

2.3 Application of systems methodology

The bibliographic references of the inquiry were selected according to the question: "How a virtual assistant understands?" The purpose is to investigate the techniques on the basis of which a virtual assistant nowadays can understand meanings from the sentences that reach it.

The search criteria applied are:

- Search engine: Scopus.
- Recent years: From 2019 to 2023.
- Keywords: Virtual assistant, natural language, NLP, machine learning, deep learning, language understanding, NLU, voice assistant, voice-controlled, smart devices, dialogue systems, deep neural networks, voice command, virtual agent, Human-Computer Interaction, speech recognition.
- Document type: Articles and reviews.
- Subject area: Computer science.
- Access: Open.

3. Inquiry

The conducted inquiry resulted in the following:

A search on virtual assistants returns more than a thousand articles. This number was reduced to 316, when the search was made more specific, by using the term "how they understand". Then, there was a further limitation, when the time span of the articles, within the last five years, was made more specific. The new number is 221 articles. By applying restrictions to the keywords (see Section 2.3), the number of articles became 137. Of these, by choosing to keep only articles and reviews, 39 remained. Then, when only those hosted in Open Access journals were kept, only 19 articles remained. The last criterion applied was computer science in the subject area. After this, the 12 articles below remained for discussion.

The 1st article [12] discusses parents' motivations for using virtual assistants (such as Amazon's Alexa or Google Assistant) with their children at home. The authors conducted interviews with parents, to understand how they use virtual assistants to support their children's learning and development.

In the 2nd study [13], the method used is Red Deer Optimization with AI-enabled image captioning system. The virtual assistant is designed to assist visually impaired people, by providing image captions that are generated using an AI algorithm. The Red Deer Optimization algorithm is used to optimize the performance of the AI model, for generating accurate and relevant image captions. The system uses deep learning techniques, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), to process and analyze images and generate captions based on the content of the images. The virtual assistant is designed to be user-friendly and can be accessed through a mobile application or a web interface.

The 3rd article [14] discusses different methods for measuring the similarity between questions in Arabic. It does not mention any specific method used for virtual assistants to understand the questions. However, measuring the similarity between questions can be a useful component of NLP.

The 4th article [15] discusses various approaches to dialogue management in conversational systems. The article reviews different methods and techniques for dialogue management, such as rule-based, model-based, and reinforcement learning-based approaches.

The 5th article [16] does not focus on any specific virtual assistant or conversational system, but rather provides a broad overview of different approaches and challenges in dialogue management. Therefore, it does not describe a specific method used by a virtual assistant to understand user input. Instead, it provides a comprehensive review of different approaches that conversational systems can use to manage the dialogue.

In the 6th article [17], the issues discussed are faced by IVAs, such as Siri, Google Assistant, Cortana, and Alexa. These issues include voice recognition, contextual understanding, and human interaction. The authors conducted a survey of 100 users to understand their experiences with IVAs. The survey found that while IVAs offer many services, there are still improvements needed in voice recognition, contextual understanding, and hands-free interaction. The article aims to address these improvements, so that the use of IVAs can be increased. The main objective of the survey was to validate the real potential of IVAs and to guide users in choosing the best personal assistant for real-life scenarios. According to the 6th article [18], the method used for the virtual assistant to understand is a "semantic web framework". This framework involves the usage of ontologies, which are structured vocabularies that define relationships between concepts, to enable the virtual assistant to understand and respond to natural language queries, related to public health. The authors describe a case study where they applied this framework to develop a smart assistant for public health, which was able to accurately answer questions related to diseases, symptoms, and treatments.

In the 7th article [19], the Capsule Net architectures are used, for Intent detection and slot filling for a Romanian home assistant. The Capsule Net architecture is a type of deep learning neural network that aims to overcome the limitations of the traditional Convolutional Neural Network (CNN), by capturing the hierarchical relationships between features. The authors used this architecture for both intent detection and slot filling, in order to improve the accuracy of the Romanian home assistant's understanding of user queries. Intent detection involves identifying the user's intention or goal behind the query, while slot filling involves identifying specific pieces of information that are relevant to fulfilling that intention or goal. The authors demonstrated that their approach using Capsule Net architectures achieved higher accuracy, compared to other state-of-the-art methods in intent detection and slot filling for the Romanian home assistant.

The 8th article [20] does not appear to describe a specific method used by virtual assistants to understand natural language. Instead, the article focuses on the role of social identity and the extended self in collaboration with virtual assistants. It explores how users perceive and interact with virtual assistants and how the assistants can be designed to enhance collaboration with users. Therefore, the article does not describe a technical method of virtual assistants for understanding natural language, but rather a theoretical framework for understanding users' behaviour and preferences related to virtual assistants.

In the 9th article [21], the authors are investigating the factors that influence users' continued use of smart voice assistants.

The 10th article [22] discusses how NLP and other supporting technologies such as IoT and AI are used to enable virtual assistants to work as real-time assistants, providing technical and social assistance to users in various modes, such as secretarial work, customer service support, and web editing tasks. The authors also designed an intelligent virtual assistant that could be integrated with Google virtual services and work with the Google virtual assistant interface, using speech recognition, a knowledge base, and machine learning techniques to make the conversation between humans and software more natural.

The 11th article [23] explores the question of why it is helpful to have a digital assistant, specifically in the context of manufacturing. The article describes the components and benefits of digital assistants, such as mobility, voice interaction, a delegation of tasks, and rapid data analysis. The article notes that developing a digital assistant can be challenging, as customers may not benefit from all of its components immediately. Additionally, it argues that digital assistants have significant potential in manufacturing, where they can help to enhance the skills and capabilities of the remaining workforce, save employees' time, and contribute to increasing work efficiency.

The last article (12th) [24] discusses a method for building scalable multi-domain conversational agents, by using the Schema-Guided Dialogue Dataset. This dataset provides a schema that defines the possible intents, slots, and dialogue actions that a virtual assistant can recognize and generate, making it easier to train and evaluate virtual assistants across multiple domains. The method used involves fine-tuning pre-trained language models, such as BERT, and training dialogue models using supervised learning techniques on the dataset. The virtual assistant can then understand user input and generate appropriate responses, based on the defined schema.

4. Discussion

According to the above inquiry and studies, it is found that, while there is extensive discussion on the use of IVAs to address various problems and proposals for increased use, few words are said about how they operate. Specifically, it is known that an IVA typically works as shown below:

1) Input: The IVA receives input from the user, usually in the form of text or voice commands.

2) NLP: The IVA uses NLP algorithms to understand the user's input and extract the relevant information.

3) Knowledge Base: The IVA accesses a knowledge base, which contains information that the IVA can use to answer the user's questions or perform a task.

4) Decision Making: Based on the user's input and the information available in the knowledge base, the IVA makes a decision about how to respond to the user's request.

5) Output: The IVA generates a response to the

user, which can be in the form of text, voice, or other types of media.

6) Machine Learning: IVAs can also use machine learning techniques to improve their performance over time. As they interact with users, they can learn from their mistakes and become better at understanding and responding to users' requests.

Overall, the goal of an IVA is to provide a personalized, efficient, and intuitive user experience, similar to interacting with a human assistant. IVAs can be used in a variety of applications. However, because IVAs are commercial products, there is not much emphasis on how they work and how they understand natural language. As a result, research mostly focuses on how these products are used. This lack of information opens up a chapter on how to apply similar capabilities to those of commercial products on newly developing robotic systems.

Such a robotic system, being developed by the authors [25-27], is based on the communicative power of the OMAS-III systemic conceptual model and uses experimentally a small natural language dictionary in Greek. Special emphasis is given to the understanding aspect, with an NLU unit based on Hole Semantics [28,29], which recognizes gaps in expressions and tries to initially fill them, either with existing knowledge it possesses, or with questions to its interlocutor. This gap recognition ability is implemented through the journalists' questions of OMAS-III (see Section 2.2). Each question corresponds both to a part-of-speech (i.e. subject, object, verb, adverb, etc.) and simultaneously to a relevant semantic slot. If a slot is empty, which means an absence of information, then a semantic hole is created that has to be filled.

Special attention is given to how the system understands time through the sentences it receives and in combination with its existing developing knowledge. Such a system could be very important in many areas of application, such as healthcare, where it can sequence events that have occurred, as well as those that need to be implemented. The evaluation of the system's performance is undergoing, and relevant data are gathered to be presented in the near future. This inquiry also highlights a significant research gap in sequencing actions, given in random order.

5. Conclusions

Through the present study, it is understood that current virtual assistants are commercial products that the information revealed a focus on their functionality and not on the technical part of achieving their functionality. They include an NLP module to manage the human-robot interaction, yet, a gap was found in the description of IVAs comprehension techniques. Additionally, a research gap remains in arranging the temporal sequence of actions that such a system has to think about; not just time management but understanding time. On this gap, the authors are going to continue and expand their previous work [26,27], which is based on the communicative power of the OMAS-III systemic conceptual model. This conceptual model is being tested along with the framework of Hole Semantics, in order to allow a robot to handle missing information. The experimental use of conceptual modelling is currently under trials.

Author Contributions

I. Giachos conducted the inquiry, classified the results and edited the text. E.C. Papakitsos monitored the usage of systemic methodology and assessed the compatibility of the research criteria to the conceptual framework of Systems Science and OMAS-III; he also supervised the usage of NLP techniques. P. Savvidis evaluated the technical part of the virtual assistants and selected the suitable ones for further investigation. N. Laskaris supervised this research project, set the assessment criteria and evaluated the methodology, as well as the overall outcome.

Conflict of Interest

The authors declare no conflict of interest.

Funding

This research received no external funding.

References

[1] Giachos, I., Piromalis, D., Papoutsidakis, M., et al., 2020. A contemporary survey on intelligent human-robot interfaces focused on natural language processing. International Journal of Research in Computer Applications and Robotics. 8(7), 1-20.

[2] Markowitz, J., 2003. Toys that Have a Voice. Speech Technology Magazine [Internet]. Available from: https://www.speechtechmag.com/Articles/ReadArticle.aspx?ArticleID=30031

[3] Juang, B.H., Rabiner, L.R., 2005. Automatic speech recognition—a brief history of the technology development. Rutgers University and the University of California, Santa Barbara. 1, 67.

[4] Gold, B., 1990. A history of Vocoder research at Lincoln Laboratory. The Lincoln Laboratory Journal. 3(2), 163-202.

[5] Lindsay, D., 1997. Talking head. American Heritage of Invention & Technology. 13(1).

[6] Suryadi, S., 2006. The "talking machine" comes to the Dutch East Indies: The arrival of Western media technology in Southeast Asia. Bijdragen Tot de Taal-,Land-En Volkenkunde/Journal of the Humanities and Social Sciences of Southeast Asia and Oceania. 162(2/3), 269-305.
DOI: https://doi.org/10.1163/22134379-90003668

[7] Deryugina, O.V., 2010. Chatterbots. Scientific and Technical Information Processing. 37(2), 143-147.
DOI: https://doi.org/10.3103/S0147688210020097

[8] Ahirwar, G.K., 2020. Chatterbot: Technologies, tools and applications. High Performance Vision Intelligence: Recent Advances. 913, 203-213.
DOI: https://doi.org/10.1007/978-981-15-6844-2_1

[9] Papakitsos, E., 2013. The systemic modeling via military practice at the service of any operational planning. International Journal of Academic Research in Business and Social Science. 3(9), 176-190.

[10] Sanders, M., 1991. Communication technology today and tomorrow. Glencoe/McGraw-Hill: New York.

[11] Παπακίτσος, Ε.Χ., 2008. Θέματα Σεμιναρίων Σχολικού Επαγγελματικού Προσανατολισμού (Greek) [Seminar Topics in School Vocational Guidance]. Αθήνα: Μ.-Χ.Χ. Χριστοδουλάτου.

[12] Saunders, M., Lewis, P., Thornhill, A., 2015. Research methods for business students (7th edition). Pearson Publication: Dallas.

[13] Wald, R., Piotrowski, J. T., Araujo, T., et al., 2023. Virtual assistants in the family home. Understanding parents' motivations to use virtual assistants with their Child(dren). Computers in Human Behavior. 139, 107526.
DOI: https://doi.org/10.1016/j.chb.2022.107526

[14] Hilal, A.M., Alrowais, F., Al-Wesabi, F.N., et al., 2023. Red deer optimization with artificial intelligence enabled image captioning system for visually impaired people. Computer Systems Science and Engineering. 46(2), 1929-1945.
DOI: https://doi.org/10.32604/csse.2023.035529

[15] Daoud, M., 2022. Topical and non-topical approaches to measure similarity between arabic questions. Big Data and Cognitive Computing. 6(3), 87.
DOI: https://doi.org/10.3390/bdcc6030087

[16] Brabra, H., Báez, M., Benatallah, B., et al., 2021. Dialogue management in conversational systems: A review of approaches, challenges, and opportunities. IEEE Transactions on Cognitive and Developmental Systems. 14(3), 783-798.
DOI: https://doi.org/10.1109/TCDS.2021.3086565

[17] Tulshan, A.S., Dhage, S.N., 2019. Survey on virtual assistant: Google Assistant, Siri, Cortana, Alexa. Advances in Signal Processing and Intelligent Recognition Systems, SIRS 2018. Communications in Computer and Information Science. 968, 190-201.
DOI: https://doi.org/10.1007/978-981-13-5758-9_17

[18] Sermet, Y., Demir, I., 2021. A semantic web framework for automated smart assistants: A case study for public health. Big Data and Cognitive Computing. 5(4), 57.
DOI: https://doi.org/10.3390/bdcc5040057

[19] Stoica, A., Kadar, T., Lemnaru, C., et al., 2021.

Intent detection and slot filling with capsule net architectures for a romanian home assistant. Sensors (Switzerland). 21(4), 1-28.
DOI: https://doi.org/10.3390/s21041230

[20] Mirbabaie, M., Stieglitz, S., Brünker, F., et al., 2021. Understanding collaboration with virtual assistants—The role of social identity and the extended self. Business and Information Systems Engineering. 63(1), 21-37.
DOI: https://doi.org/10.1007/s12599-020-00672-x

[21] Pal, D., Babakerkhell, M.D., Zhang, X., 2021. Exploring the determinants of users' continuance usage intention of smart voice assistants. IEEE Access. 9, 162259-162275.
DOI: https://doi.org/10.1109/ACCESS.2021.3132399

[22] Arora, S., Athavale, V.A., Maggu, H., et al., 2020. Artificial intelligence and virtual assistant—working model. Mobile radio communications and 5G networks: Proceedings of MRCN 2020. Springer Singapore: Singapore. pp. 163-171.
DOI: https://doi.org/10.1007/978-981-15-7130-5_12

[23] Wellsandt, S., Hribernik, K., Thoben, K.D., 2021. Anatomy of a digital assistant. Advances in Production Management Systems. Artificial Intelligence for Sustainable and Resilient Production Systems. IFIP Advances in Information and Communication Technology. 633, 321-330.
DOI: https://doi.org/10.1007/978-3-030-85910-7_34

[24] Rastogi, A., Zang, X., Sunkara, S., et al., 2020. Towards scalable multi-domain conversational agents: The schema-guided dialogue dataset. Proceedings of the AAAI Conference on Artificial Intelligence. 34(5), 8689-8696.

[25] Papakitsos, E.C., Giachos, I., 2016. The study of machine translation aspects through constructed languages. International Journal of Electronic Engineering and Computer Science. 1(1), 28-34.

[26] Γιάχος, Ι., Παπακίτσος, Ε.Χ., Μακρυγιάννης, Π.Σ., 2017. Ένα Πείραμα Εκμάθησης Γλωσσικής Επικοινωνίας σε ένα Ρομποτικό Σύστημα (Greek) [An Experiment in Learning Language Communication in a Robotic System]. The 9th Conference on Informatics in Education—Piraeus. p. 46-56. Available from: http://events.di.ionio.gr/cie/images/documents17/cie2017_Proc_OnLine/new/custom/pdf/CIE2017_proceedings_all.pdf

[27] Giachos, I., Papakitsos, E.C., Chorozoglou, G., 2017. Exploring natural language understanding in robotic interfaces. International Journal of Advances in Intelligent Informatics. 3(1), 10-19.
DOI: https://doi.org/10.26555/ijain.v3i1.81

[28] Bunt, H., 2008. Semantic underspecification: Which Technique for what purpose? Computing Meaning. 3, 55-85.

[29] Bos, J., 2002. Underspecification and resolution in discourse semantics [PhD thesis]. Saarland: Saarland University.