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HumanRoboLab: Experiments with chatbots in management education at universities

Denis Pijetlovic and Georg Mueller-Christ

Abstract. Digital dialogue systems, known as "chatbots," are an application sub-area in automation which is increasingly used in both work and business contexts. The growing use, functionality and benefits of chatbots are therefore also of interest for university teaching in economics. Students at the University of Bremen's Department of Economics are developing their own transdisciplinary chatbot project. Working together with partners from different companies within the framework of the HumanRoboLab (HRL), they explore human–machine interaction from an application-oriented perspective. The main objective of the HRL is to test a didactic concept for transdisciplinary human–machine interaction projects in order to subsequently integrate this concept into business studies and business psychology degree programs. The purpose of such a module is to provide students without prior experience in programming with the knowledge, tools and competences to research, apply and question AI technologies in a self-effective manner; in other words, the HRL aims to help students develop expertise with regard to digitization, benefiting them in both social and economic contexts. The concept of the HRL, as well as some examples of the projects and the role of AI, are outlined in this chapter in order to provide a template for university teachers who might wish to adapt these concepts.

Keywords: Chatbot, real lab, exploratory research.

1.1 AI-based Chatbots in Higher Education Teaching: Why?

The development of algorithms in the field of artificial intelligence (AI) is a category of topics in computer science aiming to map and simulate human thinking, decision-making and problem-solving behavior using computerized processes (Bendel 2020). Chatbots fall into this category because they use elements of AI to simulate human communication behavior in such a way that people can talk to them using natural language. However, such a conception of AI-based chatbots is rather limiting in the context of application-oriented higher education teaching: It is too generally formulated and assumes expertise in cognitive sciences for its operational use to be possible. To circumvent this deficit, this chapter draws on Hammond's (2017) *Periodic Table of AI* (Figure 1) in order to make the term "AI-based chatbots" suitable for practical use in higher education teaching. A German-language version of the periodic table of AI is provided by Bitkom (2018) in an online handbook. The authors make reference to Hammond's concept for systematizing AI functions: Hammond considers AI to be the combination of basic elements, similar to complementary LEGO bricks. Each AI element represents a sub-function that has historically established itself as an encapsulated functionality of a certain complexity and power. The author identifies a total of 28 AI elements that can be combined according to general criteria (Bitkom 2018, p. 15).

Hammond's tabular arrangement of all AI elements is called a "periodic table," analogous to the physical sciences. Each AI element can be assigned to one of three groups: *Assess* is dark/light green, *Infer* is yellow/orange and *Respond* is magenta.

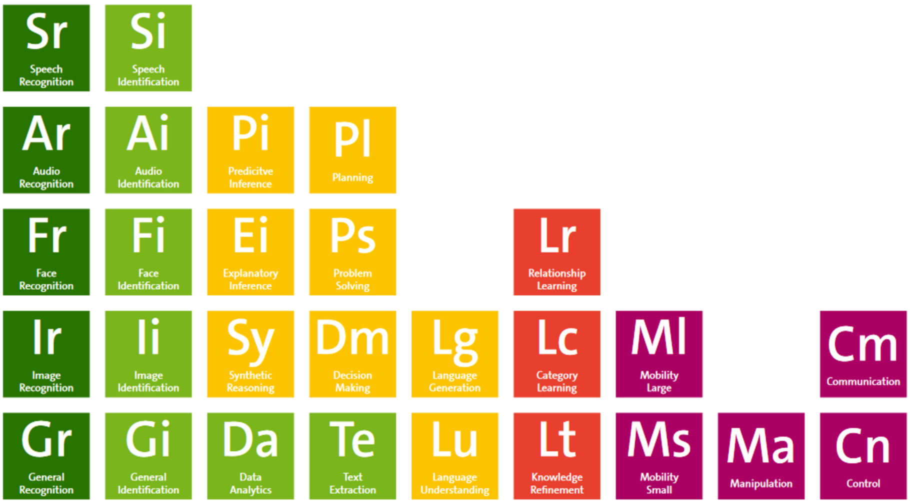

Fig. 1.1 Periodic Table of Artificial Intelligence (Source: Bitkom 2018, p. 7)

Through combinations of these different elements of AI, applications can in turn be derived and defined abstractly. In accordance with this, chatbots consist of the following AI elements:

Text extraction [Te] means that this AI element is proficient in analyzing texts. It does this by learning to differentiate between entities (e.g., people, organizations, cities, products) and terms (e.g., communication, innovation, production) in texts. This allows ambiguities in names and words to be resolved. A very everyday example of the ambiguity that AI aims to resolve would be the word *Müller*, which, depending on the context, could refer to the politician Gerd Müller, the footballer Thomas Müller, the drugstore chain Müller or simply the German word for a person who operates a mill.

Language understanding [Lu] relates to the understanding of the information in the text, that is, the assignment to meaning. This AI element captures the relationships between entities and concepts meant in texts and thus solves two problems: first, it is clarified which entities and concepts in sentence structures are actually related to one another; second, the significance of this relationship is examined. The outcome of language understanding [Lu] in combination with text extraction [Te] is the translation of a possibly ambiguous text into an unambiguous machine representation (Bitkom 2018).

Communication [Cm] as an AI element is used in turn to automatically answer large numbers of individual or recurring questions. In the course of this, models are trained based on specific case studies. These models are able to understand the meaning of incoming questions in order to suggest answers and conduct dialogs. In the case of chatbots, these data sets consist of language models that are trained by machine learning.

By fragmenting such a complex application as a chatbot, the AI periodic table helps to clarify the way in which the different elements of artificial intelligence are interrelated and work. Thus, reducing complexity by breaking it down into components with different functions helps make the broad field of artificial intelligence more workable.

1.1.1 Process support as a field of application

The areas of application for chatbots are diverse. In basic terms, chatbots are used to support people in processes and to optimize processes. These areas of application can be divided into three overarching application scenarios: (a) decision-making, (b) communication, and (c) teaching and learning processes (see Figure 2). These scenarios are considered in greater detail below.

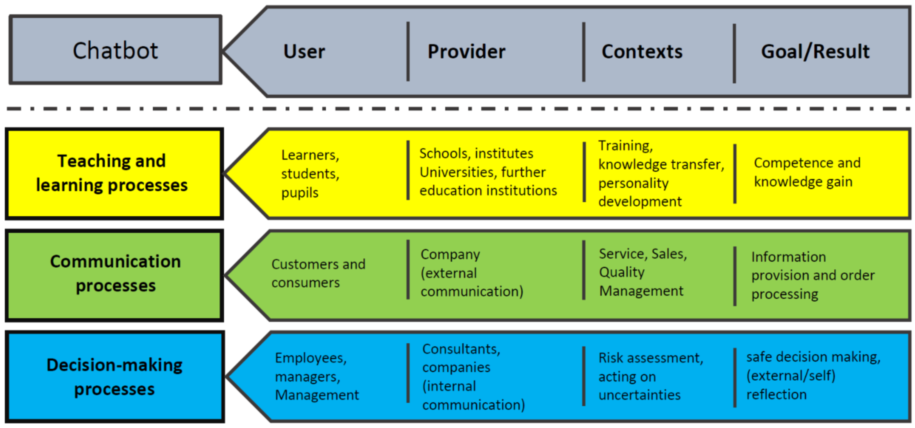

Fig. 1.2 Areas of application of chatbots in process support

(a) The use of chatbots in decision-making situations is still in its infancy. These specialized chatbots act as assistants for humans. For example, in an aerospace scenario, a decision-oriented chatbot can specify certain next (test) steps or calculate probabilities in dangerous situations. A chatbot developed by students in collaboration with OHB SE called Alan, the Astro Aid (see Chapter 4), for example, supports astronauts in resolving difficulties in handling the European Physiology Modules developed by OHB SE.

(b) Chatbots used for communication processes are primarily found in customer service. These chatbots can be used to book flights, order products or process complaints (first-level support). By using these chatbots, companies can operate more efficiently and ensure better targeted customer service.

(c) Chatbots can also be used in teaching and learning processes as virtual training partners to help students consolidate the learning material (de Witt et al. 2020, p.19). There are four different areas of application: (1) supporting learners, such as in an online community; (2) supporting learning activities; (3) testing knowledge and assessing performance; and (4) learning or career advice (Satow 2018).

1.1.2 Modeling and training of chatbots

Chatbot technology is not fundamentally new. The first prototypes were made back in the 1960s. ELIZA, developed by Joseph Weizenbaum, is considered to be the first fully functional chatbot and became known for its superficial simulation of a psychotherapist. In psychotherapy, targeted open questions are asked – a principle that

Weizenbaum used by developing a program that applies the non-directive techniques of person-centered psychotherapy according to Carl Rogers (Höltgen & Baranovska 2018). ELIZA used a structured dictionary for this, searching the sentences entered by users for terms from its dictionary. Given a matching word, the chatbot searches for generic terms or synonyms through which ELIZA can direct the conversation. Here is an example:

User: “I have a problem with my mother.”
ELIZA: “Tell me more about your family!”

This form of database query is, however, no longer comparable with what is known today as artificial intelligence (in the sense of self-learning programs). Since ELIZA, chatbot technologies have steadily evolved, particularly with conversational AI, which enables human–machine interaction through natural language and which is becoming increasingly efficient (Lamprecht 2016). Examples include AI-based applications such as OpenAI’s GPT-3, Google Dialogflow, Microsoft Luis, Amazon Lex, and IBM’s Watson Assistant. A special feature of these frameworks is that they enable even ordinary people to develop their own chatbot within a few hours without them having to be proficient in a programming language. The logic behind this technology is trivial: Chatbots are trained on specific content, known as *intents*, which are entered into the respective system. This allows the chatbots to respond to queries within seconds and enables interaction in real time. The extent to which the interaction *actually* succeeds depends on the interaction of the AI’s algorithms with the language model. A key quality feature here is the structure of the chat design: the more comprehensively the user’s possible intentions (in the form of questions, commands and small talk) can be handled, the higher the probability that the interaction will be perceived as beneficial (McTear et al. 2016).

1.1.3 Chatbots as an introduction to machine learning

In order to design an interactive chatbot, students must generate a language model for the respective case application, train it, and then optimize it based on initial test data. In this way, students can learn how machine learning (ML), a subfield of AI, works and how to control and monitor this learning process. The data for the language model is essential here. This data consists of three main parts – intents, entities and dialog – that are input into a chatbot platform. ML uses the technology known as neural networks, which are algorithms with a similar structure to the human brain. They can recognize and match recurring patterns by using all the real-world information known to them (e.g., images, texts, time sequences) to translate familiar patterns into mathematical vectors. Using neural networks, the respective system can classify new information based on similarities and combine it into entities. These entities are designated with labels, such as “customers,” “colleagues” and “order” (Roßbach 2017, p. 13 f.; Schikora et al. 2020, p. 268).

There are three different types of ML: supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, a program is given a sample data set. This contains data that is already divided into certain categories (clusters) and labeled (labeled data). In this way, the program recognizes certain input parameters and can assign them to a result. With the data thus established, it becomes a model through training runs. Once the model has been created, unknown data can be supplied to the model and the program calculates a result (prediction). In unsupervised learning, the program generates a model for a given set of inputs. This model describes the inputs and enables predictions. The input data is divided through a cluster process into several categories which differ from one another by characteristic patterns. The program is able to independently create classifications according to which it categorizes the input patterns (Gomes et al. 2017, p. 23; Schikora et al. 2020, p. 270). Reinforcement learning allows a program to independently learn a strategy based on a reward function. The reward function (or utility function) describes the value of a particular state or action. Unlike supervised learning and unsupervised learning, reinforcement learning does not require any data in advance. Instead, the database is created by trial-and-error processes within a specially created simulation scenario. During the training runs, all required data is generated and highlighted. This learning method is most similar to the natural learning method of humans (Abdoos et al. 2015, p. 213).

Supervised learning is used in the chatbot projects as part of the HRL. This is so that students learn how useful functions for the chatbot program can be created and combined from pairs of inputs and outputs. In order for the machine learning process to work, students must provide the correct function values for an input. In this way, students learn to develop context-specific (language) models. This process is iterative and is usually constantly adapted and revised until a model works satisfactorily.

1.2 Chatbot projects in the real-world laboratory

The chatbot projects carried out within the framework of the HRL (see Chapter 3) are based on experimentation in real-world laboratories (Schneidewind 2018), that is, they create a framework for "moving from knowledge to action." The ideal-typical process of the real-world laboratory according to this understanding takes place on a co-creative basis with practice partners who (1) develop the project together with the students, (2) implement the technical modeling or production of the chatbot, and (3) interpret and evaluate the outcome (Gibbons 1994; Singer-Brodowski 2016). This process reflects the concept on which the real-world laboratory approach is based: a transdisciplinary collaboration of scientists, students and practice partners with the intention of facilitating research-based learning. The context-dependence resulting from the application of knowledge enables continuous (self-) reflection and evaluation in order to repeatedly question the results and to adapt them to new conditions. Real-world laboratories are therefore learning settings for transdisciplinary exploratory research (Pijetlovic 2020; Müller-Christ & Pijetlovic 2018) that extend the usual focus of the development and application of AI technologies beyond the integration and synthesis of knowledge for potential application.

1.2.1 The HumanRoboLab concept

The HRL seeks to integrate the testing of AI technologies in the real-world laboratory into economic and business psychology courses. It aims to integrate real-world learning environments into existing modules of teaching in these subjects, enabling the use of digital technologies while at the same time promoting the development of competencies for their meaningful design and reflection. The core of the HRL concept is the dovetailing of theoretical and methodological expertise, experience, and (self-) reflection.

Such a context imparts basic specialized knowledge in the topic groups of conversation-oriented artificial intelligence and communication theories, but also promotes the practical examination of the system, target and transformation that the students apply in their respective chatbot projects. This concept is complemented by the methodological perspective of systemic exploratory research, which is composed of theories of “sciences of possibilities” (“*Möglichkeitswissenschaften*”) (Pfriem 2017) and futurology (Kreibich 2007). This interplay of theory and practice is accompanied by exercises for (self-) reflection, which not only strengthens the learning experience, but also enables a critical look at one’s own competencies and the influence of technology on human behavior. In this sense, the HRL concept attends to what is known as the “third mission” of higher education institution activities, meaning that, in addition to the other two missions of teaching and research, the higher education institution mutually interacts with the non-higher education world and uses socially relevant, reflective approaches and methods of transdisciplinary research for this purpose (Henke et al. 2016). The development of chatbot prototypes offers both students and their practice partners the opportunity not only to develop digital transformation spaces (Freiling et al. 2020) in an entrepreneurial way, but also to bring them into the socio-political context.

1.3 A selection of the chatbot projects from the HRL

The HRL concept has been integrated into the bachelor’s and master’s degree courses in Business Administration and Business Psychology at the University of Bremen. A total of 84 students have participated in the HRL to date. The courses (six/nine credit points) are offered for one semester and conclude with a public project presentation of the developed chatbot prototypes. The students give these final presentations as part of the *Digital Assistant Conference*, which can also be attended by interested company representatives. This format has already helped some students to launch their careers through their project work. Practice partners who have been involved in HRL projects to date include Sparkasse Bremen AG, the aerospace technology group OHB SE, Techniker Krankenkasse, Beiersdorf AG, Universum GmbH, the University of Bremen, EWE AG, and Seghorn AG, which specializes in receivables management, as well as the tourism development of the city of Bremen. Students were free to decide which practice partners should support the work on their respective projects.

Below is a small selection of the projects from the HRL, providing a sampling of the practical contexts for which the students have already developed fully functional chatbots.

1.3.1 TiKay Bot (Techniker Krankenkasse)

The TiKay bot optimizes the search for a space in a care home. By requesting specific information about the type of care, focus of care, level of care and location of the care home desired, during the course of a chat, TiKay can compile a list of suitable care homes based on a database. This pre-selection gives searchers an informative overview of potentially suitable facilities and allows them to focus on contacting the selected providers. In addition, the TiKay bot is able to answer general questions on topics such as costs, services, and care support, or to establish direct contact with the source of the information.

1.3.2 Museum Bot XT-9U (Universum GmbH)

The XT-9U is a chatbot for the Digital Worlds area at the interactive museum Universum in Bremen, Germany. The XT-9U has knowledge about AI and robotics. Museum visitors learn from the chatbot itself what kind of AI it is based on, and what sensors are used by robots such as Pepper and NAO (developed by SoftBank Robotics) to be able to hold a conversation. The XT-9U is based on the model of an interested scientist who wants to discover new things and also likes to scrutinize visitors’ answers. The digital assistant’s name is inspired by the Star Wars robots R2D2 and C3PO. The XT in XT-9U stands for eXtendend Technology, the 9 for its development year 2019, and the U for Universum – the name of the interactive museum.

1.3.3 DESIGN THINKING BOT (University of Bremen)

The task of the Design Thinking bot is to support participants in a design challenge based on the rules of design thinking throughout the development process of their products. This chatbot knows the individual process steps of design thinking and can guide the participants through the phases, answer questions about the process, and give useful tips for processing steps. The particular challenge of this project was to develop a chatbot that does not specify any requirements, but rather provides useful suggestions and encourages users to think creatively.

1.3.4 ALAN (OHB SE)

Alan is a chatbot developed in collaboration with the OHB Group. Alan is designed to support astronauts in space in solving problems and addressing faults quickly and efficiently. Unlike experts on Earth, he can answer any questions without any delay in the transmission of the conversation, meaning that he enables real-time support. The focus of this bot project is the service element manufactured by OHB for the International Standard Payload Rack based on the European Physiology Module. This module is designed for experiments and represents an important research facility of the Columbus space laboratory on the International Space Station (ISS). In the first application scenario, Alan was used to help astronauts correct a power circuit fault that had already occurred on the ISS in 2010 and was made apparent by the fact that the power distribution unit no longer properly worked.

1.4 Competencies and skills learned

As part of the chatbot projects in the real-world laboratory, the students were able to acquire competencies (see Table 1) that, among other outcomes, enable them to better assess the relevance of dealing with chatbots in various areas of application, to clear up misunderstandings in the debate about AI and chatbots, and to better understand media reporting of AI developments and correctly classify them. In all chatbot projects, two key competence areas were prevalent. First is the generation of datasets in order to be able to set up and subsequently train an appropriate language model. These datasets can be compiled based on structured or unstructured data. The students in the real-world laboratory primarily generated unstructured data, which they then placed in if–then relationships to enable clear sequences of intents (input) and dialog (response). This process of data structuring is necessary because the chatbot program lacks simple background information that human users naturally bring to any communications. For example, users know that people greet each other when they first meet and only then interact in more depth, but a chatbot must first be taught this socio-culturally based convention through appropriate sequences of intents and dialog. The challenge for students is to become aware of self-evident things like these and to then prepare the data in such a way that enables successful meaningful interaction for a specific purpose. The second area of competency concerns the chatbot's satisfactory performance. For each case study that the chatbot is expected to master through appropriate interaction, the AI must also be able to identify the objective of the respective user and match it with a corresponding process of solution-oriented action. This is the only way that the interaction can ultimately lead to an outcome that is actually useful to the user.

The students therefore first develop an algorithm, that is, a rule that dictates how certain goals can be achieved step-by-step. In AI, an algorithm is a rule for solving a (mathematical) problem that has been translated into a programming language. The participants in the real-world laboratory conduct expert interviews in order to better understand the processes that the chatbot is expected to support, but also to generate suitable data sets for a language model tailored to exactly these processes. In this way, the student teams were able to gain initial experience in process analysis and modeling of language models – two key competencies for the confident use of AI.

Table 1.1 Areas of competence of students in the HRL context

Area	Competency
Methodical	**- Machine learning (supervised learning)** - Data acquisition management - Dialog management
Technical	**- Knowledge of how digital dialog systems (chatbots) work** - Practical procedural knowledge regarding modeling strategies - Systemic perspective on AI
Personal	**- Development of an inquiring attitude towards AI applications** - Self-awareness from dealing with AI - Transfer of practice-oriented ideas to digital applications

By participating in the HRL, the students were able to find out whether a job in the field of chatbot development (or more generally in working with AI applications) would suit them personally, and whether after completing their chatbot project they would like to continue professionally developing in the direction of machine learning, user interaction design or conversational user experience design. At the same time, the practice partners were able to record their own learning thanks to their work on the chatbot projects. The transdisciplinary approach of the real-world laboratory has contributed to: (a) a culture of creativity and innovation, stimulating the exchange of knowledge between higher education teaching and business practices; (b) a better understanding among practice partners of chatbot technology and acquisition of transformational knowledge for their field; and (c) the opportunity for everyone involved to gather practical experience in collaborative agility.

1.5 What is next for the chatbot laboratory?

A look at the literature and visits to the corresponding platforms on the internet show that chatbots are experiencing explosive growth in the higher education sector, although many examples give the impression that the technology is mostly used to deal with very simple dialogs and rule-based tasks. Chatbots commonly encountered in higher education are used to help students deal with tasks with predefined rules, such as in mathematics or learning a new language. For language acquisition, chatbots are used as dialog partners for practicing conversational scenarios or increasing vocabulary. The work of Bao (2019) provides insight into this area regarding the reducing of fear of foreign languages through chatbot interactions. There are also chatbots in higher education that provide support with administrative tasks. An example of this can be found in the study by Galko et al, (2018), where the enrollment process for students has been completely transitioned to a dialog with a chatbot.

These types of chatbots nevertheless involve predefined applications, and can't be configured by users for their individual learning process. For higher education, therefore, these simple use cases are first steps, but they are far from maxing out the potential of AI. The presumably long road to successful (process/learning) support by chatbot systems should contribute to learners being able to reflect more on their own process of learning and deepen it in a self-directed manner. We believe that no one can solve this problem better than the students and learners themselves. What they need for this, however, is the knowledge and skills to develop such a chatbot as a learning companion in order to independently determine which learning goals are to be achieved and through which route. The assumption and hope is that, in this way, the AI potential of chatbots will be able to contribute to the development of greater learning and understanding among people and machines alike.

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