

Chatbot-mediated Learning: Conceptual Framework for the Design of Chatbot Use Cases in Education

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Keywords: Chatbots in Education, Chatbot-mediated Learning, Conversational Learning, Pedagogical Conversational Agents, Tutorial Dialogue.

Abstract: While chatbots or conversational agents are already common in many business areas, e.g. for customer support, their use in the education sector is still in its infancy. Chatbots might take over the role of a teacher, tutor, conversational partner, learning analyst, team member, support assistant, or recommender system. Within these different roles, chatbots can enhance learning and inherently address many requirements and success factors for learning. The scalability and adaptiveness of conversational AI allow an individualised learning support for all learners combined with collaboration opportunities and thus more equality in education. In this context, the paper at hand discusses this pedagogical potential of chatbots in different roles and social settings resulting in a conceptual framework for the understanding and design of chatbot use cases in education. Based on success factors for learning derived from established learning theories and reports, core attributes and goals of chatbot learning are deduced within three pedagogical domains of individual, social and analytic chatbot learning. By combining this pedagogical dimension with a technological and content dimension, the presented conceptual framework provides an overview of possibilities of how chatbots in education can be used and designed.

1 INTRODUCTION

The educational use of chatbots – chatbot-mediated learning – is an emerging research field in education. Chatbots are artificial intelligence (AI) based programs that aim to simulate human conversation (Garcia Brustenga et al., 2018). It can be assumed that such conversational agents are also suitable for certain tasks in the field of education and learning. To date, however, chatbots are not yet widely used in education. The aim of this research paper is set in this context. To advance the pedagogical implementation of chatbots in education, it is important to find out what has already been done, to structure this knowledge and make it understandable for pedagogical practice. This specific research stream is interdisciplinary and addressed by researchers from fields like computer science, education, linguistics, psychology, and business informatics. This leads to complementary but different research procedures and evaluation approaches (Hobert, 2019).

From an educational perspective it seems essential to further identify what pedagogical uses and capabilities a chatbot has in an educational

context. In this circumstance, it is also relevant to discuss the different roles and settings in which a chatbot can be useful (e.g individual or team learning situations) in relation to success factors for learning. In addition, for the design of chatbot use cases, it is fundamental to consider the technological maturity and integration into educational systems to enhance the chatbot's capabilities.

Research in this direction seems sensible for several reasons. On the one hand, there are promising pedagogical possibilities and on the other hand, one can address future skills and competences. Visible learning and the individual support of learners by teachers or human tutors are somewhat neglected due to large course sizes and an emerging number of online learning scenarios. Both, learning theories and empirical learning studies suggest the relevance of learner-centred learning, individual support, a culture of inquiry, continuous feedback and monitoring, formative feedback, and so on (Bransford et al., 2000), (Hattie & Yates, 2013). International frameworks for 21st-century learning suggest that critical thinking, making judgments and decisions, clear communication, collaboration, and

technological awareness are crucial competencies in the future (ISTE, 2017). Chatbots might support learners to develop, improve and reflect these competencies. Furthermore, students work hand in hand with digital assistants, which becomes standard in future work activities. The authors of the book “Human + Machine. Reimagining Work in the Age of AI” argue that humans need new skills to work with smart machines and that we need a deeper understanding of the complementary human-machine interaction (Daugherty & Wilson, 2018): “Humans are needed to develop, train, and manage various AI applications. In doing so, they are enabling those systems to function as true collaborative partners. For their part, machines in the missing middle are helping people to punch above their weight, providing them with superhuman capabilities, such as the ability to process and analyse copious amounts of data from myriad sources in real-time. Machines are augmenting human capabilities” (p. 6).

Within this paper, we focus on the pedagogical foundations of human-machine interaction with chatbots in education and address the following research questions: *RQ1. What pedagogical benefits and capabilities do chatbots have in an educational context? RQ2. How can a framework for the use of chatbots in education be conceptualized?* The goal is to elaborate and communicate the potential of AI-based chatbots to function as an individual or collaborative learning partner and to augment student’s capabilities. Based on the state of research (section 2) we present a conceptual framework aiming at providing a pedagogical basis for the educational use of chatbots (section 3) before we conclude with final remarks.

2 RESEARCH ON CHATBOTS IN EDUCATION

Based on the stated research goal, we identify research on intelligent chatbots in general and research on chatbots in education as relevant.

2.1 Research on Intelligent Chatbots

While the first chatbot named Eliza was already developed over 50 years ago by Weizenbaum (1966), the major developments have happened in recent years. Core technologies or components of modern chatbots like automated speech recognition (ASR), natural language processing (NLP) and text-to-speech engines rely on deep learning neural networks

and thus AI technologies. Due to technological milestones and the increasing attention to AI, chatbots, also known as conversational agents or natural dialog systems, are an emerging field of interest in many areas such as e-commerce, health, finance, service industries, and education. From a business perspective chatbots mainly allow to improve customer service and to reduce service costs, from a user’s perspective important motivations to use chatbots are productivity, entertainment, social factors and novelty interaction (Adamopoulou & Moussiades, 2020).

Examples of modern and widely known chatbots are Amazon’s Alexa, Apple’s Siri, Microsoft’s Cortana or Google Assistant, which can also be categorized as personal assistants mostly used for customer service and information acquisition or as a user interface for mobile devices (Cahn, 2017). Adamopoulou and Moussiades (2020) offer a detailed chatbot categorization and differentiate between informative, conversational or task-based chatbots to point out the main goal of the chatbot. A further basic categorization of chatbots can be the knowledge domain. Some chatbots have one or more specific knowledge domains, whereas a generic chatbot is designed to answer any user question. While we refer to both categories as chatbots, other researchers with a more technical perspective prefer the umbrella term ‘conversational systems’ and then differentiate between more domain- or task-specific ‘dialog systems’ and generic ‘chatbots’ (cf. Chen et al., 2017). An example for a generic and state-of-the-art chatbot that has won the Loebner Prize Turing test for best chatbot several times in recent years is Mitsuku (<https://kuki.ai/>). Services like IBM Watson or Google Dialogflow offer platforms and frameworks for companies or institutions to build and train domain-specific chatbots based on transfer learning techniques. The chatbot already knows how to learn (pre-trained) and is fed with domain-specific knowledge and rules for its specific use case. This allows customization and personalization of the chatbot based on a given basic structure. Most chatbots are set on a retrieval-based approach, where responses are generated based on pre-trained rules and matched through machine learning classification tasks. While such retrieval-based models promise accurate and correct responses in case of a correct match, they are unable to answer unseen questions or intents without predefined responses or actions (Winkler & Söllner, 2018). This problem can be solved with generative models, the newest generation chatbots. Generative models do not answer with predefined answers but try to generate their answers

based on the context, previous dialogs, and a pretraining based on real dialogs (Cahn, 2017). The amount of available dialog data is therefore a key success factor for underlying deep learning models. Only intensive training enables a chatbot to recognize and adapt patterns in human dialogs based on statistically frequent answers (Spierling & Luderschmidt, 2018). Retrieval-based models are considered as more reliable until today due to simplicity, while generative models are better for text generation and promise a more real conversation (Molnar & Szuts, 2018). On the downside, the generative model can only be as good as its underlying training data. So, if the data is flawed, corrupted or biased, so is the chatbot. This may be one reason why the two approaches are increasingly combined.

Considering this technical side and development of chatbots we can draw on recent studies defining technical dimensions to categorize educational chatbots (Winkler & Söllner, 2018), (Molnar & Szuts, 2018):

- 1) *Building approaches*, where retrieval-based models are distinguished from generative models. While the former are based on a set of predefined responses, using an algorithm to select the best-matching response, the latter generates responses based on the input.
- 2) *Input mode of chatbots*, in particular the question of whether speech over text input might be appropriate for our context and learning design.
- 3) *Inclusion of contextual information*, such as for example time, location, user information, learning path data, in order to select the right responses.

From an ultimate technological perspective, the goal of a chatbot and consequently the evaluation focus might be to pass the so-called Turing test (cf. Turing, 1950), meaning that the optimal chatbot cannot be distinguished from humans. Cahn (2017) mentions further perspectives to evaluate performance: From a user experience perspective another goal would be user satisfaction, from a linguistic perspective a goal would be for the chatbot to speak grammatically correct and meaningful and from an information retrieval perspective chatbots should also be evaluated according to the specific function (Cahn, 2017). In an educational context, this function and therefore the evaluation perspective might differ again from case to case but would additionally include learning outcome, learning success, and learner motivation.

2.2 Chatbots in Education

In recent years the spread of chatbots and the research on chatbot development, design, and use has increased and advanced. Følstad et al. (2020) are convinced that chatbots are maturing for application areas including education and may be designed for individual users or for supporting collaboration. Previous research on chatbots in education often focuses on designing messenger-like chatbots but there might be a lack on generalizable results (Meyer von Wolff et al., 2020). Winkler and Söllner (2018) conducted an extensive literature review and conclude that “the effectiveness of chatbots in education depends on individual student differences, the ways of building chatbots, and the chatbot mediated learning process quality” (p.29). While the authors consider only few studies that suggest the potential of chatbots for learning purposes so far, they also emphasize the great potential of chatbots to create individual learning experiences for students and to support teachers. The exploration of this potential in the field of technology-mediated learning – chatbot-mediated learning – is a growing and interdisciplinary research field. It can however, draw on a rich body of previous research in different educational research fields around pedagogical agents and tutorial dialogue systems. Research in this field suggests that both, support by a tutorial dialogue agent and collaborative learning support lead to better learning outcomes than supportless learning (Kumar et al., 2007).

Compared to traditional intelligent tutoring systems or pedagogical agents in e-learning scenarios, chatbots do not only give instructions or provide feedback, but can also react to individual intents and create a real personalization and more importantly, a learner-centred approach (Winkler & Söllner, 2018). While these technologies can be integrated and build on each other, chatbots can be regarded as conversation technologies that have a more stand-alone character compared to adaptive learning systems. Chatbots in education can still have different user interfaces or be embedded in other systems like a Learning Management System (LMS). The main difference between chatbots in education compared to other contexts is probably the integration or self-storage of learning objects or even learning paths (Hobert, 2019). Figure 1 illustrates a technical setup of a chatbot in an educational setting in a high-level abstraction.

With the ultimate goal to enhance and enable a learner-centred individual and collaborative learning setting, chatbots promise to have a positive impact on

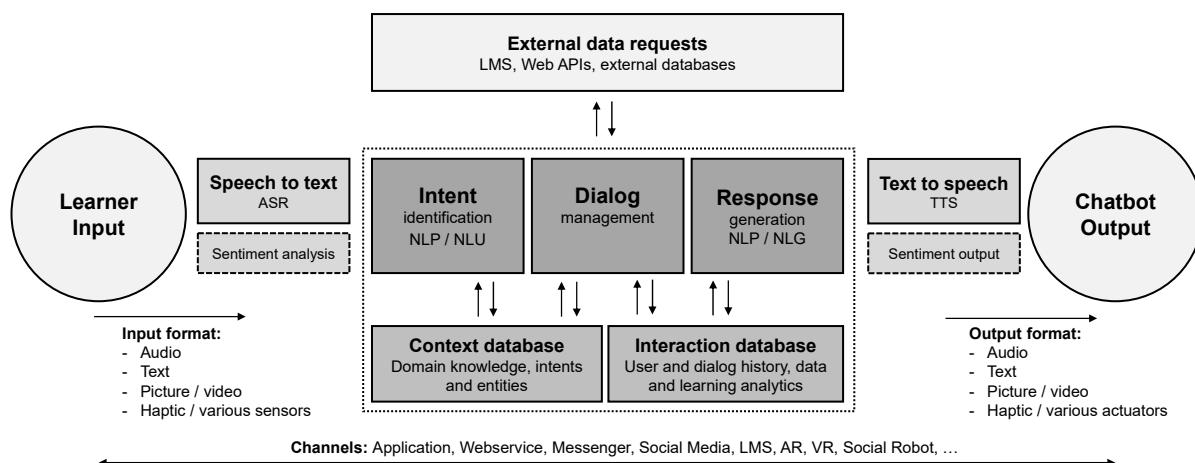


Figure 1: Educational Chatbot Model. (cf. Seufert et al., 2021).

student motivation, satisfaction, and learning success (Winkler & Söllner, 2018). In education practice, however, the productive use of chatbots is still in its infancy. Nevertheless, research groups see great potential of chatbots in education and present promising use cases for different tasks such as learning assessments, reflections, language learning, motivating, mentoring, administration, or productivity assistant (Garcia Brustenga et al., 2018).

Most studies, that have shown successful implementations of chatbot learning scenarios (cf. Dutta, 2017; Goel et al., 2016; Huang et al., 2017), are based on projects with isolated chatbot tasks, e.g. to answer frequently asked questions, to handle forum posts, or to ask questions in language learning applications. Language learning is a more advanced application of chatbots in education. Fryer et al. (2019) summarize that in early research chatbots as language practice tools were shown to be useful for advanced and motivated students, but showed limitations in terms of in- and output quality. More recent research shows, that the linguistic quality has improved significantly and that chatbot conversations are carried on longer but with fewer words and vocabulary within messages compared to human-human conversations (Fryer et al., 2019).

Another example of more advanced chatbot use cases in education is supporting students with course and administrative information or offering screening tests via chatbot. This application is already implemented at universities worldwide but can, at least until today, be considered more of a customer service chatbot use case than chatbot-mediated learning. Within a comprehensive conceptual framework, such use cases could in a further sense be assigned to educational recommender systems. These are seen as electronic systems containing domain

knowledge, learner information, and knowledge of the teaching strategies which seek to improve learning (Bodily & Verbert, 2017). A future chatbot might also combine and integrate the intelligence of the different student-facing learning analytics systems distinguished by Bodily and Verbert (2017): Learning Analytics Dashboards, Educational Recommender Systems, Educational Data Mining Systems, Intelligent Tutoring Systems. Another related approach addressing the integration of AI technologies in education is cognitive computing in education, where a cognitive assistant (e.g. a cognitive bot) would combine different AI services (Lytras et al., 2019).

As introduced in section 2.1, there is still the question of how to evaluate educational chatbots in terms of learning outcomes, learner motivation, learner satisfaction or other constructs. Winkler and Söllner (2018) propose a learning taxonomy model (Anderson, 2001) as a basis for the evaluation of learning outcomes, further evaluating the influence of chatbots on self-efficacy and self-regulation skills. Within 25 studies reviewed in the field of chatbot-mediated learning, Hobert (2019) identified 7 evaluation objectives (acceptance and adoption, learning success, motivation, usability, technical correctness, further psychological factors, and beneficial effects) and matched the objectives with the main research procedures identified (Wizard-of-Oz experiment, technical validation, laboratory experiment, field experiment). The author emphasizes that most studies analyse only selected aspects and he attributes this to the interdisciplinarity of this field (Hobert, 2019). This fact supports the aim of this paper to present a comprehensive framework and to provide a basis for future research projects that evaluate the use of chatbots beyond single evaluation objectives.

3 CONCEPTUAL FRAMEWORK

Within this section, we present a conceptual-level framework to understand chatbot-mediated learning and to design pedagogical chatbot use cases. The goal of the presented framework is to lay out what pedagogical uses and capabilities a chatbot has in an educational context. Hence, the presented framework can offer a foundation for the conceptual and pedagogical design of chatbot use cases and to uncover the further potential and limitations of the underlying technologies within education.

Table 1: Chatbots in Education – Maturity Levels.

TPACK	Level 1	Level 2	Level 3
Pedagogy	Individual chatbot learning	+ Social chatbot learning	+ Metacognition and analytics
Technology	Simple rule-based chatbot	+ Supervised learning AI + Sentiment	+ Unsupervised learning AI / Generative
Content	Domain knowledge Chatbot	+ Social/context knowledge	+ Omniscient

Note: Categories based on TPACK model (Koehler & Mishra, 2009)

The structure of the presented framework is based on the Technological Pedagogical Content Knowledge (TPACK) model, which is widely used in educational research. The TPACK model originally represents a framework for teacher knowledge for technology integration Koehler and Mishra (2009). Even though a chatbot should primarily be learner-

centred it also should integrate these same three and closely connected components of educator knowledge. Table 1 gives an overview of the three components by which we study chatbots in education and in a first step indicate high-level maturity levels.

The theoretical background in section 2 has shown that present chatbots in education are mainly designed for personal learning and as conversational partners or tutors, with an information retrieval approach based on domain knowledge (maturity level 1-2). Future chatbots might include more collaborative learning, analytics (cf. Ifenthaler & Schumacher, 2016) and metacognition functions, use more advanced AI and generative models, and additionally retrieve and process social and context information (maturity level 2-3).

3.1 Pedagogical Perspective and Goals

With a focus on educational maturity, we intend to substantiate the potential of chatbot learning with learning theory in the form of connections with established learning theories and more recent learning reports and empirical studies (Table 2). A corpus of learning-related theories (Bandura, 1997; Deci & Ryan, 2012; Leventhal et al., 1984) and reports (Bransford et al., 2000; Hattie & Yates, 2013; ISTE, 2017) was chosen based on broad acceptance in educational research and related based on its key concepts and constructs for learning success. Table 2 illustrates the pedagogical perspective and theoretical deduction of core attributes and goals of chatbot

Table 2: Chatbots in Education – Pedagogical Perspective and Goals.

	Individual chatbot learning	Social chatbot learning	Metacognition & analytics
<i>Core attributes and goals of chatbot learning based on underlying learning theories and reports</i>	Personalized and needs-based learning Individual learning pace	Collaboration and network memory Social embedding	Learning progress and formative assessment Feedback & reflection
<i>Self-determination theory (Deci & Ryan, 2012)</i>	Autonomy experience	Social relatedness	Competence experience
<i>Self-efficacy / social cognitive theory (Bandura, 1997)</i>	Self-Mastery; Self-Regulation	Role-Modelling; Verbal persuasion	Self-Efficacy; Feedback
<i>Self-regulation theory (Leventhal et al., 1984)</i>	Self-Reflection	Team-Reflection	Metacognition; Monitoring
<i>How to learn (Bransford et al., 2000)</i>	Learner centred; considered learn path	Culture of inquiry	Assessment centred; continuous monitoring
<i>Framework 21st century learning (ISTE, 2017)</i>	Communication skills; decision making	Collaboration skills; creativity; empathy	Critical thinking; Use of technology
<i>Visible learning (Hattie & Yates, 2013)</i>	Feedback; Self-Verbalisation	Reciprocal teaching (dialog based)	Formative evaluation; Meta-cognitive strategy

Table 3: Conceptual Framework for Chatbots in Education.

Dimensions	Characteristics (can be met supplementary)			
Pedagogical dimensions				
Chatbot role in individual learning setting Cf. (Garcia Brustenga et al., 2018)	Support assistant e.g. research assistant, FAQ, Nerdybot	Conversational partner e.g. communication trainer, tutor	Recommender system e.g. learning path recommendations	Learning analyst e.g. formative assessment
Chatbot role in social learning context Cf. (Garcia Brustenga et al., 2018)	Teacher e.g. storytelling, debater, presenter, teaching assistant	Team member e.g. maintain project documentation, team support, research	Collaboration enhancer e.g. connect teams, structure teamwork	Team analyst e.g. analyze teamwork and provide feedback
Learning Analytics Cf. (Fryer et al., 2019; Ifenthaler & Schumacher, 2016)	Summative assessment (ask questions and give feedback)	Formative assessment (reflect on learning progress, continuous feedback)	Intelligent edu-recommender system (continuous learning process monitoring)	Emotion analytics (Monitor and analyse sentiments /emotions to improve learning)
Technological dimensions				
Human-Computer Interaction Cf. (Spierling & Luderschmidt, 2018)	Visual based (e.g. text)	Audio based (e.g. speech)	Virtual presence (e.g. virtual agent)	Physical presence (e.g. robot)
Intelligence Cf. (Lytras et al., 2019; Molnar & Szuts, 2018)	Simple rule-based model	Retrieval-based model	Generative models and unsupervised learning models	Social intelligence: Sentiment analysis, emotion detection
Embedding / Channel	Local application (mobile / computer)	Webservice (on any device)	Social Media (known channel)	Embedded in LMS (on any device)
Content dimensions				
Contextual data integration Cf. (Molnar & Szuts, 2018; Winkler & Söllner, 2018)	Basic domain knowledge database	Basic context data (time, location, user)	Personalisation with conversation history	Personalisation with learner information (learner path /grades)
Knowledge base Cf. (Anderson, 2001)	Factual domain knowledge	Conceptual and procedural knowledge	Knowledge representation	Metacognitive and social knowledge

learning. The bullet point attributes and goals included, describe elementary principles and success factors for learning and create a basis for linking chatbot learning with concrete didactic goals. They thus help in the justification of chatbot learning and as a conceptual basis for concrete goals and their evaluation.

3.2 Conceptual Design of Chatbot Use Cases in Education

At the beginning of a project to design and use a chatbot in education, the following questions are of central importance in connection with the objective:

- What are the (pedagogical) goals of the chatbot use? What is the context?
- Which target group does the chatbot address?
- What is the role and what are the tasks of the chatbot? What is the role of the learner?
- What are the limitations or technological requirements? What (sensitive) data is used?

- What is the time, personnel and financial budget?

Since chatbot projects in education, just like innovations in learning technologies, are often driven by a technological direction, it is recommended to combine the pedagogical with the technological perspective at an early stage to develop a shared new vision of learning (Dillenbourg, 2016). Based on the pedagogical perspective from section 3.1 one can identify the educational setting and define desired learning conditions and pedagogical goals in order to answer the questions posed.

Accordingly, in table 3 we lay out the core of the conceptual framework for the conceptual design of chatbot use cases in education, based on the pedagogical perspective from section 3.1 and the theoretical and technical background from section 2. The three components of the TPACK model serve as the main structure. The goal is a collectively configuration of the pedagogy, technology and content dimensions. Each dimension has four

characteristics that can be met supplementary (e.g. a chatbot can have the role of a conversational partner and a learning analyst combined, or be available over multiple channels).

When planning a chatbot use case in education, the pedagogical point of view is central together with the goal of the chatbot use. The role of the chatbot in an individual or social learning setting already partly determines the further requirements. At the same time, the roles or tasks that a chatbot can take on in practice today are often limited by the technological possibilities and boundaries. An extensive overview as well as practical examples of chatbots in education divided by tasks is provided by Garcia Brustenga et al. (2018). When it comes to developing a chatbot in education, Satow (2019) describes the following development steps:

- Creating the bot concept
- Analysis of real dialogs and questions
- Creation of bot scripts
- Bot training by defining intents
- Bot skills development
- Testing the chatbot
- Optimize in productive use

When designing chatbot dialogs, general and education specific design principles can be helpful (cf. Yu et al., 2016). Cahn (2017) describes 'human imitation strategies' that have proven successful (e.g. personality development, conversation control, human errors). And in terms of developing a chatbot for learning purposes, Smutny and Schreiberova (2020) offer a list of attributes describing the quality of an educational chatbot within the categories teaching (e.g. set goals and monitor learning progress), humanity (e.g. able to maintain themed discussion), affect (e.g. entertaining, engaging) and accessibility (e.g. responds to social cues appropriately).

From a technological point of view, in addition to the form of interaction and chatbot intelligence, the main question is its integration or embedding. Educational institutions such as schools and universities as well as educational organisations in companies often use learning management systems. Here it is important to clarify whether the chatbot can be integrated into existing learning platforms or, if other channels are used, how the learner authenticates himself to the chatbot, if necessary. This is especially important if the chatbot is to access not only general knowledge (factual, conceptual, procedural or social) but also contextual knowledge about the individual learner from a content perspective. This can be, among other things, personal, performance-related or

behavioural data. The data basis and its use result in limiting factors and requirements, which are discussed in the following section 3.3.

3.3 Limitations

Depending on the role of the chatbot, data storage or connection to databases, it is important to clarify the topics of data protection, data storage, data security, data integrity and data deletion at an early stage. Since AI services are often computing power-intensive and therefore cloud-based, the privacy of the individual is all the more important (Walsh, 2018). According to (Cahn, 2017), chatbots via messenger applications or services are problematic from a privacy perspective, as services such as Facebook Messenger do not offer end-to-end encryption by default and cannot guarantee user identification. At the same time, many chatbots and services include and process sensitive data (personal data, images, audio, video). Services such as Amazon Echo store recordings in the cloud, while many other services send the data for further processing unencrypted via APIs. All these factors speak in favour of in-house development and local data storage and processing. Nevertheless, researchers also emphasise advantages of smart assistants or messaging applications such as a familiar user interface, no installation, no costs, integration of games, sharing of media (Smutny & Schreiberova, 2020). Regardless of the technology chosen, there are ethical issues to discuss. In addition to data protection, there is an important demand for explainable AI (XAI), which is particularly important in the field of education (Gunning, 2017). Zanzotto (2019) calls for responsible AI with a "human-in-the-loop" and a clear knowledge life cycle to prevent a bias of the AI or the chatbot.

4 CONCLUSIONS

Chatbots and conversational AI have the potential to go beyond the pure simulation or imitation of human interaction as defined in the introduction. They can enhance human beings and learners in many possible ways, individually or in groups, within a classroom or outside, in business, in education, and daily life. The human-machine interaction with chatbots in education promises a variety of pedagogical advantages and possibilities. Chatbots enable personalized learner-centred and needs-based learning, a main success factor for learning, for student motivation and contribution according to

learning theory and studies. In a collaborative role, chatbots promise to improve and enhance collaboration skills, social embedding and team-reflection. And based on learning analytics and access to context knowledge including learning paths, chatbots may make learning visible, improve metacognitive strategies and foster learner's confidence and self-reflection through continuous monitoring and feedback.

With the presented conceptual framework, we provide an overview of possibilities how chatbots in education can be used. The framework might help to conceptualize a chatbot use case and underlying pedagogical goals based on a configuration of the presented dimensions covering the pedagogical, technological, and content perspectives of an educational chatbot. Besides the highlighted pedagogical potential of chatbots in education, we want to point out limitations regarding our framework as well as chatbots in education in general. While the framework presents a high-level understanding and idea of the configuration, it does not address the implementation process and its various obstacles that require utmost attention, e.g. data privacy and protection, data life cycle, copyrights, integration issues on institution level, biases, information quality, dependence on big technology suppliers, ethical and legal questions and so on.

Future research could consider and focus on these factors and the implementation phase of concrete use cases while building upon the conceptual framework and its underlying concepts and learning theories. From a pedagogical and interdisciplinary perspective, it would be interesting to work towards a more comprehensive evaluation of various success factors and basic conditions for learning, in addition to specific evaluations of chatbots in terms of individual measurable target variables.

REFERENCES

- Adamopoulou, E., & Moussiades, L. (2020). Chatbots: History, technology, and applications. *Machine Learning with Applications*, 2(53), 100006. <https://doi.org/10.1016/j.mlwa.2020.100006>
- Anderson, L. W. (Ed.). (2001). *Pearson education. A taxonomy for learning, teaching, and assessing: A revision of Bloom's Taxonomy of educational objectives* (Abridged ed.). Longman.
- Bandura, A. (1997). *Self-efficacy: The exercise of control*. Freemann.
- Bodily, R., & Verbert, K. (2017). Review of Research on Student-Facing Learning Analytics Dashboards and Educational Recommender Systems. *IEEE Transactions on Learning Technologies*, 10(4), 405–418. <https://doi.org/10.1109/TLT.2017.2740172>
- Bransford, J. D., Brown, A. L., & Cocking, R. R. (2000). *How people learn: Brain, mind, experience, and school. Expanded edition*. National Academy Press.
- Cahn, J. (2017). *CHATBOT: Architecture, Design, & Development*.
- Chen, H., Liu, X., Yin, D., & Tang, J. (2017). A survey on dialogue systems: Recent advances and new frontiers. *Acm Sigkdd Explorations Newsletter*, 19(2), 25–35.
- Daugherty, P. R., & Wilson, H. J. (2018). *Human + machine: Reimagining work in the age of AI*.
- Deci, E. L., & Ryan, R. M. (2012). Self-Determination Theory. In P. van Lange, A. Kruglanski, & E. Higgins (Eds.), *Handbook of Theories of Social Psychology: Volume 1* (pp. 416–437). Sage Publications. <https://doi.org/10.4135/9781446249215.n21>
- Dillenbourg, P. (2016). The Evolution of Research on Digital Education. *International Journal of Artificial Intelligence in Education*, 26(2), 544–560. <https://doi.org/10.1007/s40593-016-0106-z>
- Dutta, D. (2017). *Developing an Intelligent Chat-bot Tool to Assist High School Students for Learning General Knowledge Subjects*. Georgia Institute of Technology. <https://smartech.gatech.edu/handle/1853/59088>
- Følstad, A., Araujo, T., & Papadopoulos, S. (2020). *Chatbot Research and Design: Third International Workshop, CONVERSATIONS 2019, Amsterdam, The Netherlands, November 19–20, 2019, Revised Selected Papers* (1st ed. 2020). *Information Systems and Applications, incl. Internet/Web, and HCI*. <https://doi.org/10.1007/978-3-030-39540-7>
- Fryer, L. K., Nakao, K., & Thompson, A. (2019). Chatbot learning partners: Connecting learning experiences, interest and competence. *Computers in Human Behavior*, 93, 279–289. <https://doi.org/10.1016/j.chb.2018.12.023>
- Garcia Brustenga, G., Fuertes Alpiste, M., & Molas Castells, N. (2018). *Briefing Paper: Chatbots in Education*. Universitat Oberta de Catalunya (UOC). <https://doi.org/10.7238/elc.chatbots.2018>
- Goel, A., Anderson, T., Belknap, J., Creeden, B., Hancock, W., Kumble, M., & Wilden, B. (2016). Using Watson for Constructing Cognitive Assistants. *Advances in Cognitive Systems*, 4.
- Gunning, D. (2017). Explainable artificial intelligence (xai). *Defense Advanced Research Projects Agency (DARPA), Nd Web*, 2, 2.
- Hattie, J., & Yates, G. C. R. (2013). *Visible Learning and the Science of How We Learn*. Routledge.
- Hobert, S. (2019). *How Are You, Chatbot? Evaluating Chatbots in Educational Settings – Results of a Literature Review*. 10.18420/DELFI2019_289
- Huang, J., Lee, K., Kwon, O., & Kim, Y. (2017). A chatbot for a dialoguq-based second language learning system. *CALL in a Climate of Change: Adapting to Turbulent Global Conditions*, 151.
- Ifenthaler, D., & Schumacher, C. (2016). Learning Analytics im Hochschulkontext. *WiSt* -

- Wirtschaftswissenschaftliches Studium*, 45(4), 176–181. <https://doi.org/10.15358/0340-1650-2016-4-176>
- ISTE. (2017). *ISTE standards for students*. <https://www.iste.org/standards/standards/for-students>
- Koehler, M., & Mishra, P. (2009). What Is Technological Pedagogical Content Knowledge? *Contemporary Issues in Technology and Teacher Education*, 9, 60–70.
- Kumar, R., Rosé, C. P., Wang, Y.-C., Joshi, M., & Robinson, A. (2007). Tutorial dialogue as adaptive collaborative learning support. *Frontiers in Artificial Intelligence and Applications*, 158, 383.
- Leventhal, H., Nerenz, D. R., & Steele, D. F. (1984). Illness representations and coping with health threats. *A Handbook of Psychology and Health: Sociopsychological Aspects of Health*, 219–252.
- Lytras, M., Visvizi, A., Damiani, E., & Mathkour, H. (2019). The cognitive computing turn in education: Prospects and application. *Computers in Human Behavior*, 92, 446–449. <https://doi.org/10.1016/j.chb.2018.11.011>
- Meyer von Wolff, R., Nörtemann, J., Hobert, S., & Schumann, M. (2020). Chatbots for the Information Acquisition at Universities – A Student’s View on the Application Area. *Chatbot Research and Design - 3rd International Workshop, 2019, 11970 LNCS*. https://doi.org/10.1007/978-3-030-39540-7_16
- Molnar, G., & Szuts, Z. (2018). The Role of Chatbots in Formal Education. In *IEEE 16th International Symposium on Intelligent Systems and Informatics (SISY)* (pp. 197–202). IEEE. <https://doi.org/10.1109/SISY.2018.8524609>
- Satow, L. (2019). Lernen mit Chatbots und digitalen Assistenten. In A. Hohenstein & K. Wilbers (Eds.), *Handbuch E-Learning*. Wolters Kluwer.
- Seufert, S., Guggemos, J., & Sonderegger, S. (2021). Soziale Roboter im Bildungsbereich. In O. Bendel (Ed.), *Soziale Roboter* (Vol. 22, pp. 475–494). Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-31114-8_25
- Smutny, P., & Schreiberova, P. (2020). Chatbots for learning: A review of educational chatbots for the Facebook Messenger. *Computers & Education*, 151, 103862. <https://doi.org/10.1016/j.compedu.2020.103862>
- Spierling, U., & Luderschmidt, J. (2018). Chatbots und mediengestützte Konversation. In C. Kochhan & A. Moutchnik (Eds.), *Media Management* (pp. 387–408). Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-23297-9_22
- Turing, A. M. (1950). Computing Machinery and Intelligence. *Mind*, LIX(236), 433–460. <https://doi.org/10.1093/mind/LIX.236.433>
- Walsh, T. (2018). *It’s alive: Wie künstliche Intelligenz unser Leben verändern wird*. Edition Körber.
- Weizenbaum, J. (1966). ELIZA: A computer program for the study of natural language communication between man and machine. *Communications of the ACM* 9(1966),1."Computational Linguistics" S. 36-45.
- Winkler, R., & Söllner, M. (2018). *Unleashing the Potential of Chatbots in Education: A State-Of-The-Art Analysis*. 10.5465/AMBPP.2018.15903abstract
- Yu, Z., Xu, Z., Black, A., & Rudnicky, A. (2016). Strategy and Policy Learning for Non-Task-Oriented Conversational Systems. *Proceedings of the 17th Annual Meeting of the Special Interest Group on Discourse and Dialogue*. <http://doi.org/10.18653/v1/w16-3649>
- Zanzotto, F. M. (2019). Human-in-the-loop Artificial Intelligence. *Journal of Artificial Intelligence Research*, 64, 243–252.