Introducing Vicky: A Pedagogical Conversational Agent for the Classification of Learning Styles

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Abstract. Learners are faced with the challenge of processing a large amount of knowledge. However, they often lack individual support, and teaching is not tailored to their learning styles. Conversational Agents (CAs) could be a way to identify personal learning styles through a dialog between the CA and the learner, and to support him/her accordingly. This paper investigates whether learning styles can be determined through a dialog with a CA and how the conversation is perceived by users. For this purpose, a CA called Vicky was developed using the platform Rasa and the intent classifier DIET. Vicky determines the user's learning styles through a questionnaire as well as a quiz and acts human-like to be perceived as a virtual companion. The prototype was evaluated in an experiment with 25 participants. They predominantly perceived themselves to be correctly classified and treated kindly by the CA. Overall, we contribute to science and practice by showing that CAs acting as virtual companions can be used to better understand learner preferences.

Keywords: Conversational Agent, Virtual Companion, Education, Learning Style Classification

1 Introduction and Motivation

School and university students have to process and remember a large amount of knowledge during their academic life. However, in many educational institutions, there is a lack of personalized support for learners, and teaching is not tailored to their individual preferences [1–3]. Research suggests that learners have different learning styles, which characterize learner preferences (e.g., in how knowledge is presented) and can be assessed through questionnaires [1, 4]. The technology-assisted adaptation of the instruction of learning content to learning styles could be a way to tailor teaching to the individual needs of learners and thus contribute to solving the problems outlined [1, 5]. Conversational Agents (CAs) can be used to identify learners' needs and provide them with individual support [6, 7]. CAs are intelligent dialog systems (e.g., chatbots) that can communicate with their users using natural language [8]. One example is the virtual learning tutor "*Oscar*", which determines learning styles in a tutoring session and teaches computer science knowledge adapted to the identified learning styles [1]. The

research relevance of pedagogical CAs has increased significantly in recent years [7, 9]. In addition, the CA design in general has evolved as well. Whereas classical approaches such as "*Siri*" fulfilled especially assistance functions, novel CAs like "*Replika*" can establish a friendly, companion-like relationship with users, interacting with them emotionally, and thus fostering their trust [10, 11]. Virtual companions are characterized by the fact that they interact with their users as co-equal partners [11], rather than as tutors as in the case of Oscar [1]. Despite the great potential of CAs, many interactions with them are not motivating [12]. Gamifying the dialog by incorporating game elements could be one way to stimulate the conversations, although gamified CAs are still underrepresented in research [ibid.]. While there are existing approaches for learning style detection by CAs [1, 13], there is a lack of corresponding solutions incorporating companionship properties [9]. To address the identified issues (lack of personalized teaching based on learning styles; existing CAs are less stimulating), we developed and evaluated a CA called "*Vicky*" as part of a Design Science Research (DSR) project. Vicky is a level 1 artifact [14] that determines learning styles via a companion-like conversation consisting of a questionnaire as well as a quiz game.

2 Design of the Artifact

We developed the artifact using "*Rasa*", an open-source platform for designing CAs, which enables the quick implementation of a CA as well as its integration with external services. Furthermore, we used "*DIET*" (Dual Intent and Entity Transformer) as the entity extractor and intent classifier. Rasa contains further intelligent functions for interaction design, e.g., an entity synonym mapper to enable the use of synonyms, or a fallback classifier to handle messages that cannot be unambiguously assigned to an intent. The dialog with the CAs is entirely in English and text-based. Therefore, we integrated the CA into the "*Telegram*" platform to create an interface to a well-used messenger service. Established design knowledge for CAs, especially from the Information Systems domain, was used to enable a rigorous design of the artifact [14]. E.g., the CA exhibits human-like traits (such as name or communication behavior) and addresses the user personally to build a personal bond [15]. Vicky interacts in an overall friendly and at the same time transparent manner to build trust by explaining the aims of the interaction (classification of learning styles) [3, 16]. When the user wonders about the relevance of the dialog or whether he/she is communicating with a human or a machine, the CA sets out the aim of the dialog in a kindly, motivating, and transparent manner [16]. We also added a chitchat with Vicky telling jokes to keep the dialog interesting [3]. However, to fulfill the objective of the dialog, the CA leads the user back to the classification of learning styles as soon as the chitchat gets too in-depth (see Fig. 1).

The CA uses the FS model of Felder and Silverman [17] to identify learning styles. We chose this model because it has already been used in technology-enhanced learning [13] and is scientifically validated [1]. The FS model indicates that learning styles lie on a continuum of the following dimensions: *sensing/intuitive* (preference for intaking information), *visual/verbal* (preference for presenting information), *active/reflective* (preference for processing information), and *sequential/global* (preference for

understanding information) [17]. The recognition of learning styles is done with a reduced version (17 items) of the "*Index of Learning Styles*" (ILS) questionnaire, which was also used as well as validated by Latham (2011) [1]. During the interaction, the learner has to choose one answer option for each question. If he/she is uncertain regarding the preference of an option, Vicky explains to choose the option that is most likely to apply. The CA remembers the selected answers through natural language understanding and calculates the corresponding set of learning styles at the end of the conversation based on logical rules [17]. Vicky also informs the user about the result of the questionnaire, explains the identified learning styles step by step and advises the learner on how to optimize his/her learning process accordingly. Based on the FS model, it is also possible that the learner might exhibit a balanced learning style for some dimensions [1, 17]. To stimulate the interaction [12], questions are embedded in a storyline of an initial small talk as well as questions about the learner's personality and everyday study life. Furthermore, the CA builds common ground during the dialog to promote the perception as a virtual companion [11], e. g.: '*You are a pretty cool person*'. In doing so, the CA shows sympathy and exhibits active listening [11, 15], e.g.: '*You said at the beginning that you remember your activity from yesterday as a picture*'.

To refine the classification of learning styles, as well as to gamify the dialog [12], we integrated a quiz game in which the learner has to solve certain tasks step by step (also called "*scaffolding*") [6] Based on the behavior in finding the solution, learning styles are classified again [1]. Learning styles can be described by a small number of characteristics, e.g., visual learners prefer to have content presented visually through pictures or videos [1, 17]. If learners tend to answer questions correctly after watching a video, this indicates a preference for visual learning content [1]. The identification of learning styles is also based on logical rules. For this purpose, four different question types were chosen, which are based on the FS model [1, 17]: *practical questions* (e.g., math problems), *theoretical questions* (to test knowledge and understanding), *process questions* (to check whether the learner prefers to be guided through a process while working on the solution), and *trick questions* (to test attention). If learners respond to practical questions directly, this promotes an *active and sensory learning style*. If learners wish to be guided through the process when asked process questions, this indicates a *sequential and reflective learning style*. Correctly answering theory questions favors a *reflective and intuitive learning style*. Responding properly to trick questions indicates that learners are good at focusing their attention, which favors a *sensory and verbal learning style*. Learners can answer quiz questions directly or request help through a button. If the answer is correct, Vicky informs the user about it and congratulates him/her to foster motivation. In case of a wrong answer, different aids (e.g., pictures, videos, texts) are offered, and depending on what the learner chooses, this influences the learning style classification along with the logical rules. The concrete quiz questions were developed in a joint discussion among the authors to design generally applicable exercises.

Fig. 1 exemplifies the design of the CA, consisting of the ILS questionnaire, the quiz game, and the chitchat. In addition, the following demo video illustrates the artifact: https://youtu.be/BykICWZ_M2o.

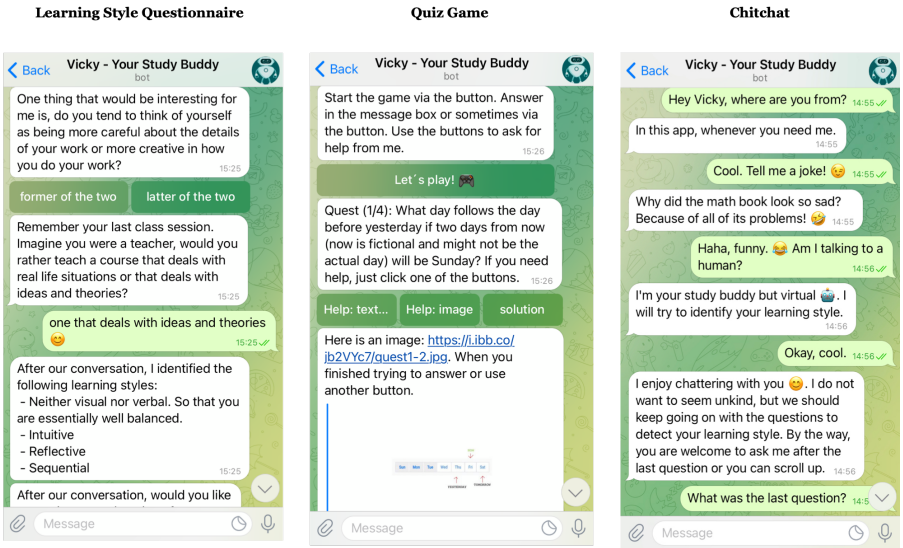

Fig. 1. Excerpts of the Conversation with Vicky

3 Evaluation of the Artifact

We evaluated the artifact through a laboratory experiment so that participants could ask questions in case of technical challenges. The 25 participants (female: 8, male: 17, avg. age: 26) tested the CA (questionnaire and quiz game) and answered an online survey. We assessed the general interaction with Vicky as well as the comprehensibility and the subjective correctness of the learning style classification [4]. In addition, we asked open-ended questions to assess the users' overall impression.

In general, interaction and comprehensibility were evaluated positively. All participants perceived Vicky's questions as understandable. On average, the quiz questions were considered to be difficult, but this was necessary for Vicky to capture the reaction to the offered aids. Most participants had no problems in understanding the quiz questions, but some lacked background knowledge in solving the math tasks. E.g., they did not know some terms like the median, but Vicky explained them through scaffolding. The majority of the participants (n = 21) did not feel the need to abort the conversation. Four participants wanted to quit because they felt misunderstood by the CA due to the quiz length and the answers given. Slightly less than half of the participants (n = 11) found both interactions equally entertaining. Almost a third preferred the dialog based on the ILS questionnaire (n = 8). The remaining participants (n =6) enjoyed the quiz the most. In general, the results show that Vicky is mostly correct in assessing learning styles. 24 out of 25 participants felt that they had been correctly assessed by the CA and were satisfied with the identified classification, as it was perceived as realistic. However, classification via questionnaire was not only more fun but also evaluated better, i.e., participants felt that they were better classified ($MV_{Questionnaire}$ = 5,24 vs. MV_{Quiz} = 4,74 with a seven-point Likert scale from 1 = extremely disagree to 7 =

extremely agree). Finally, participants could mention positive aspects and improvement suggestions regarding our artifact. The CA was associated with the following positive aspects: fast, understandable, friendly, helpful, motivating, fun, and authentic. However, a few participants still perceived the interaction to be time-intensive, not yet human-like enough, and inflexible, so we could gain feedback for future improvement.

4 Conclusion

Significance to Research and Practice: The use of learning style classification is not new to individualize teaching so that learners are optimally supported in studying [e.g., 1, 13]. However, to the best of our knowledge, our proposed CA is the first artifact incorporating companionship properties as well as two different options for classification (questionnaire and quiz) to enable a stimulating dialog. Therefore, our research is a first step towards exploring the design of learning style classification with a CA to really provide an added value in learning environments while motivating learners. The evaluation results indicate that users perceived their classification as correct, with more agreement on the classification via questionnaire.

Technological progress is accelerating the development and distribution of CAs in a variety of contexts, such as education [3, 7, 9]. As adaptive and personalized learning can be seen as the future of online education [3, 7], our research contributes to further evidence to the notion that classification of learning styles via CAs is possible as a way to learn more about the learners and their preferences. This could also be extended to other forms of needs assessments, such as surveying personality types to make learning truly adaptive, personalized, and oriented towards achieving learning success.

Limitations and Outlook: While this paper already provides initial findings, it also has some limitations. Only a small number of participants (n = 25) engaged in the experiment, and they were asked to subjectively assess whether their learning style classification by Vicky was correct. However, this was necessary to gain training data in an experimental setting following the recommendation of Latham (2011) [1]. An evaluation with a larger sample is already planned. In some cases, participants' intentions were not well understood, so that they wanted to quit the interaction (n = 4). Therefore, we integrated more buttons to provide choices and increase comprehension [18]. However, it is also important to collect more training data. Currently, the interactions with Vicky are a bit inflexible, so an interruption could hinder a complete classification of the learning styles. As a next step, we plan to refine Vicky's language comprehension as well as the quiz questions. Overall, additional design cycles are necessary to provide rigorous knowledge [14]. For this purpose, we plan an iterative development with the integration of further training data that involves an evaluation with a larger sample.

In summary, our novel artifact as well as the findings from its evaluation provide insights into how CAs can be used for technology-enhanced learning.

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References

1. Latham, A.M.: Personalising Learning with Dynamic Prediction and Adaptation to Learning Styles in a Conversational Intelligent Tutoring System. (2011).
2. Seaman, J.E., Allen, I.E., Seaman, J.: Grade increase: Tracking distance education in the United States. Babson Survey Research Group. (2018).
3. Wambsganss, T., Söllner, M., Leimeister, J.M.: Design and evaluation of an adaptive dialog-based tutoring system for argumentation skills. In: Proceedings of the 41st International Conference on Information Systems (ICIS). Hyderabad, India (2020).
4. Felder, R.M., Soloman, B.A.: Index of learning styles. (1991).
5. Luan, H., Tsai, C.-C.: A review of using machine learning approaches for precision education. Educational Technology & Society. 24, 250–266 (2021).
6. Winkler, R., Hobert, S., Salovaara, A., Söllner, M., Leimeister, J.M.: Sara, the Lecturer: Improving Learning in Online Education with a Scaffolding-Based Conversational Agent. In: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems. pp. 1–14. Association for Computing Machinery, New York, USA (2020).
7. Karrenbauer, C., König, C.M., Breitner, M.H.: Individual Digital Study Assistant for Higher Education Institutions: Status Quo Analysis and Further Research Agenda. Presented at the Wirtschaftsinformatik 2021 Proceedings. Essen, Germany (2021).
8. Gnewuch, U., Morana, S., Maedche, A.: Towards Designing Cooperative and Social Conversational Agents for Customer Service. In: Proceedings of the 38th International Conference on Information Systems (ICIS). Seoul, South Korea (2017).
9. Khosrawi-Rad, B., Rinn, H., Schlimbach, R., Gebbing, P., Yang, X., Lattemann, C., Robra-Bissantz, S.: Conversational Agents in Education – A Systematic Literature Review. In: Proceedings of the 30th European Conference on Information Systems (ECIS). Timișoara, Romania (forthcoming).
10. Xie, T., Pentina, I.: Attachment Theory as a Framework to Understand Relationships with Social Chatbots: A Case Study of Replika. In: Proceedings of the 55th Hawaii International Conference on System Sciences (HICSS). Maui, USA (2022).
11. Strohmann, T.: From Assistance to Companionship-Designing Virtual Companions. (2021).
12. Benner, D., Schöbel, S., Süess, C., Baechle, V., Janson, A.: Level-Up your Learning – Introducing a Framework for Gamified Educational Conversational Agents. In: Wirtschaftsinformatik 2022 Proceedings. Nürnberg, Germany (2022).
13. Dağ, F., Geçer, A.: Relations between online learning and learning styles. Procedia - Social and Behavioral Sciences. 1, 862–871 (2009).
14. Gregor, S., Hevner, A.R.: Positioning and presenting design science research for maximum impact. MIS quarterly. 37, 337–355 (2013).
15. Liebrecht, C., van Hooijdonk, C.: Creating Humanlike Chatbots: What Chatbot Developers Could Learn from Webcare Employees in Adopting a Conversational Human Voice. In: Følstad, A., Araujo, T., Papadopoulos, S., Law, E.L.-C., Granmo, O.-C., Luger, E., and Brandtzaeg, P.B. (eds.) Chatbot Research and Design. pp. 51–64. Springer, Cham (2020).
16. Wambsganss, T., Höch, A., Zierau, N., Söllne, M.: Ethical Design of Conversational Agents: Towards Principles for a Value-Sensitive Design. In: Wirtschaftsinformatik 2021 Proceedings. Essen, Germany (2021).
17. Felder, R.M., Silverman, L.K.: Learning and teaching styles in engineering education. Engineering education. 78, 674–681 (1988).
18. Han, E., Yin, D., Zhang, H.: Interruptions during a service encounter: Dealing with imperfect chatbots. In: Proceedings of the 42nd International Conference on Information Systems (ICIS) (2021).