Caught in the Lifelong Learning Maze: Helping People with Learning Analytics and Chatbots to Find Personal Career Paths

Atezaz Ahmad*, Natalie Kiesler, Daniel Schiffner, Jan Schneider, and Sebastian Wollny

***Abstract*—Current lifelong learning platforms offer users a query option to select a wide variety of courses. However, finding a suitable course among the seemingly endless catalogs of options presented by the platforms is not straightforward. We argue that digital counseling can enhance this process. In this paper, we present a set of three formative studies where we explored the main aspects that can provide the counseling needed. The methods comprise an analysis of user profile characteristics and learning analytics indicators (e.g., learning progress/self-regulation) by means of an expert workshop, evaluating the feasibility of current technologies (e.g., natural language processing) for automatically assessing users' competencies, and a survey on the use of Chatbots as the interaction interface between the users and the lifelong learning portals. The analysis resulted in the extraction of basic requirements for digital counseling. We conclude the paper by presenting a system design derived from these studies.**

***Index Terms*—Learning analytics, indicators, dashboard, Chatbot, lifelong learning, natural language processing**

I. Introduction

Lifelong learning is the continuous development of knowledge and skills, which happens throughout a lifetime [1, 2]. It plays an essential role in improving societal and individual well-being [3] and increases the employability, adaptability, and mobility of educated professionals [4]. Moreover, it helps professionals, such as IT experts, in keeping up with important technological advances like new programming languages, which tend to appear faster in recent years [5, 6].

In contrast to primary, secondary, and higher education, lifelong learning is currently a primarily decentralized process. To provide learners with an overview of learning opportunities, portals for lifelong learning courses [7–9] were established in Germany. However, finding suitable courses is not straightforward: Learners need to be aware of their competence level [10], translate their learning desires into keywords, and perform a respective selection of suitable courses. This process is usually accompanied and guided by counseling via trained personnel and hence is limited by the availability of these.

We argue that the enhancement of lifelong learning portals with digital counseling can help to address the previously mentioned challenges. We propose three driving technologies for the implementation of this digital counseling that helps people to navigate toward their desired career path. First, we consider it important to have a user profile that stores and visualizes the competencies of the users, where competency is the set of knowledge, cognitive abilities, skills, and dispositions of an individual in the context of a task [11, 12]. With the help of Learning Analytics (LA) techniques, this profile can show/visualize the users' current and projected learning progress. LA refers to the collection, analysis, and reporting of learners' data for understanding and improving learning [13]. It has been acknowledged that LA Dashboards (LADs) play a role in learners' academic performance, understanding level, self-regulated learning, and academic motivation [14–16].

Second, for the competencies that are not explicitly stated or whose level is not well defined in the user profile, we contemplate the option of having a light assessment that can help users to find available courses suitable for their competency level and in turn update their profile. Finally, to provide digital counseling, we opt for the interaction between user and portal to be mediated by a Chatbot, as it has been shown that Chatbots have the potential to function as mentors in educational settings [17].

This paper presents several preliminary evaluations where we explored the suitability, feasibility, and design concepts for the use of the three aforementioned technologies in the development of a digital counseling solution for a lifelong learning portal. We guided our research through the following research questions:

The main research question is: how can we support learners in finding suitable courses through digital counseling?

To answer this overarching research question, we derived the three following ones that are linked to our proposed driving technologies to support digital counseling.

Concerning the creation of user profiles for a lifelong learning platform, first, we want to know the important characteristics of the user profiles that lead to our first research question.

RQ1: What user-profile characteristics based on LA instruments can be used to help learners find more suitable courses?

It is not feasible to manually create light assessments for all competencies and available courses. Hence we want to explore whether technological advancements can help automate this process leading to our second research question.

RQ2: To what extent can we use Natural Language Processing (NLP) techniques to automatically extract questions for the light assessment?

To build a Chatbot that supports digital counseling for lifelong learning, it is important to address some of its constraints and main features, thus leading to our third research question.

Manuscript received September 25, 2022; revised October 23, 2022; accepted November 23, 2022.

The authors are with the DIPF | Leibniz Institute for Research and Information in Education, Frankfurt, Germany.

*Correspondence: a.ahmad@dipf.de (A.A.)

doi: 10.18178/ijiet.2023.13.3.1822

RQ3: What characteristics of Chatbots are relevant to providing learners with counseling regarding the course selection process?

II. Current Solutions

There are several non-commercial, state-supported information portals where course providers can promote their training and users can search for lifelong learning courses. The main goal of lifelong learning portals is to provide easy access to information and knowledge to help users to find further educational courses. In this context, traditional German open lifelong learning portals (see Fig. 1) usually collect information about available learning materials (courses, seminars, etc.) from different providers and store them in a central database. The main feature of respective *platforms* is a meta-search engine, which offers courses for further education of any kind, whereas course providers may be commercial and non-commercial. Users can then query the database to search for courses based on filters such as topics, location, schedule, etc. In some cases, such as the state-supported IWWB portal (German "InfoWeb Weiterbildung", in English "InfoWeb Further Education"), users have to select a suitable course out of over three million course offerings [7]. Other examples of further education portals are the portal provided by the state of Hesse, Germany, with more than 15 thousand course offerings [8], and the further education portal by the federal government of Germany, with more than 28 thousand course offerings [9]. All three examples are publicly available. We are currently not aware of comparable portals that are commonly used in other countries and regions.

In contrast to these portals, there are several other commercial or semi-commercial, non-open platforms related to lifelong learning who offer the search for their own lifelong learning courses, for example:

- Khan Academy [18]: a non-commercial online learning platform based in the United States that relies on the use of a search bar for users to find courses free of charge.
- Coursera [19]: a commercial platform started in the United States, which offers university-level courses and certification programs that use categorized search and registration is required to find courses.
- Iversity [20]: a commercial platform based in Berlin, Germany, that provides online courses and higher education lectures that rely on a search bar for users and categories to find learning materials.
- Futurelearn [21]: another commercial online learning platform based in the United Kingdom that offers course categories and a search bar to find relevant courses.
- Linkedin Learning [22]: formerly known as Lynda.com, is a commercial educational platform based in the United States. They use profile logs and Artificial Intelligence (AI) to recommend courses to get a dream job. Due to their commercial nature and the lack of respective research, the approach can neither be evaluated nor replicated.

In-depth analyses and comparisons of MOOC platforms for lifelong learning are presented in [23–25]. The main difference is that the German lifelong learning portals are open (i.e., search without registration), supported by the government, and they combine different course providers and their offers.

With such a huge amount of offerings, finding a suitable course that will support the further professional development of users is not straightforward. With the exception of a few cases that also provide basic course recommendations, most current platforms expect the user to hopefully find a suitable course in the ocean of available courses with the use of basic search functionalities. Therefore, we propose to enhance lifelong learning portals via digital counseling.

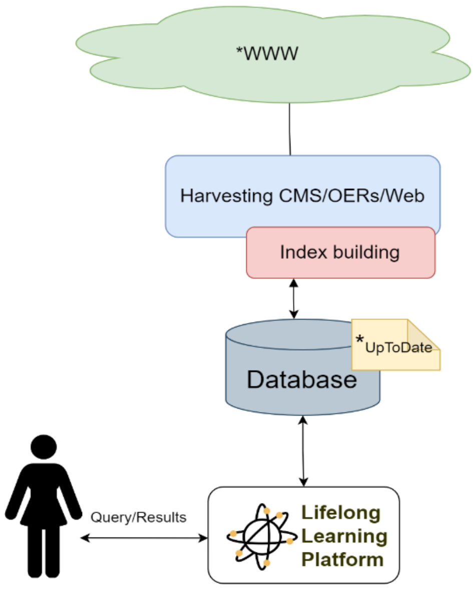

Fig. 1. Lifelong learning platform system architecture. Users query the underlying database by formulating queries or following prestructured pages.

III. Method

To realize digital counseling, which can enhance a lifelong learning portal, the plan is to follow a design-based research methodology. This is an iterative process whose objective is to support the development of solutions and interventions to complex problems [26]. In this paper, we present the preliminary findings that will lead to the design and development of the prototypes that will be developed for the first iteration.

For the investigation of basic requirements for the content and visualizations of the user profile mentioned in RQ1, we conducted a *profile workshop* with 15 experts in the field of technology-enhanced learning. Experts were divided into three groups of five persons each. They had 45 minutes to use their expertise in LA to design a dashboard that will allow the users to visualize their competencies so that it can support users in the search for suitable lifelong learning courses. To design such a dashboard, we asked the participants to use both Google Drawing [27] and Open Learning Analytics Indicator Repository (OpenLAIR) [28] for selecting relevant LA indicators. OpenLAIR is a LA tool that helps course designers, teachers, students, and educational researchers to make informed decisions about the selection of learning activities, LA indicators, and metrics or measurements for their course design or LA dashboard [28].

We then wanted to explore whether lifelong learning portals need to create an individualized user profile or if they could import generic user profiles. Therefore, in a second step, we analyzed the fields and metadata available at Europass [29], which is an online platform designed to create and share Curricula Vitae. We investigated to what extent an integration with such a platform can be used to create a user profile that helps with lifelong learning digital counseling considering the basic requirements of the user profiles extracted from the *profile workshop*.

To examine the use of NLP techniques for the automatic extraction of light assessment, we evaluated the metadata of the course description of the available "JavaScript" courses in IWWB [7] and in the following books [30–32] following the methods and scripts defined in [33], that leverage artificial jabbering for automatic text comprehension question generation. The restriction to programming languages has been made in advance to reduce the overall set of possible hits.

To explore the relevant characteristics of Chatbots to provide lifelong learners with counseling regarding the course selection process, we also conducted an exploratory survey with 89 university students where we asked the following questions:

1) Have you ever searched for further training online (seminar, course, etc.)?
2) Do you already have some experience with Chatbots? Chatbots are applications that allow you to chat with a technical system (e.g., Siri, Amazon customer service).
3) Assuming you could use a Chatbot to find a suitable course, which features would be important to you?
4) What data are you willing to share with a Chatbot?
5) Which courses should the Chatbot display to you?

Besides the survey, we held a Chatbot workshop with the experts in technology-enhanced learning. As part of the workshop, we asked them to design the communication flow chart of users interacting with a Chatbot in three groups of five, whereby the aim of the Chatbot was to help users find suitable courses. Experts had 45 minutes to complete this task.

IV. Results

RQ1: The designs of the three groups within the profile workshop pointed out the relevance of knowing the metrics or measurements that determine the different competency levels of a user. For example, the number of courses taken in a programming language (metrics) will help to determine the programming competency of the user (indicator) [34]. All three groups considered presenting these competencies as a spider chart. They argued that this indicator could help users to achieve the desired career path (see Fig. 2.). Two groups mentioned the relevance of showing in the dashboard visualization how taking the available courses would impact their current competency level.

The mockup of the first group further proposed a weight balance scale visualization. This feature allows users to select courses from a list of available options that are aligned with their desired competencies. Once a course is selected, the scale then visualizes the impact that the selected course has in helping the user to achieve their desired competency level. This group also proposed to use a word cloud (also known as a tag cloud) visualization of the users' skills, experience, and keywords that may help understand the level of a user. Furthermore, they proposed the use of a visualization, where it is possible to compare the current competencies of the user against the competencies from the desired career path of the user that could be extracted from job offerings.

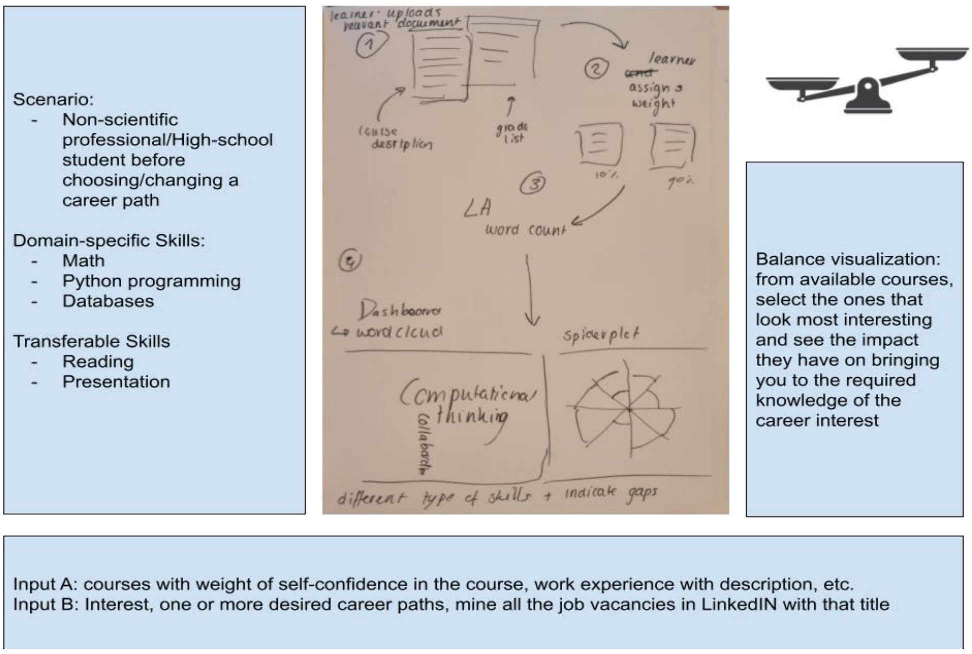

Fig. 2. Mock-up design of the first expert group.

We examined the metadata included in Europass to see to what extent such an open profile can help with digital counseling for lifelong learning. In the case of language learning, the Europass profile has excellent metadata because it includes the already established Common European Framework of Reference (A1 to C2) for each of the languages included in the users' profiles. For all other competencies, most data fields are free text where users type the title of their job or the studies. Important information to determine the competencies of the user, such as the contents of the courses taken or job tasks, is missing. Therefore, in its current state, the data from Europass is not automatically processable and hence not very helpful in providing digital counseling in this regard.

RQ2: To answer our RQ2 concerning the use of NLP, we automatically extracted questions for a potential light assessment, i.e., a rough estimation of the competency level. As a first step, we looked at the available "JavaScript" courses in several databases and the respective information provided in the course description. This way, we identified 1316 different offerings. We then analyzed the description of 20 randomly selected course offers. On average, the course description was 279.45 words long with a standard deviation of 309.5. The course with the longest description had 1450 words, and the one with the shortest description had 38. The examination of the descriptions revealed that 12 of them included logistics about the course offering e.g., number of sessions, schedule of the sessions, etc. Eight of them included information about the relevance of the course and the discussed technologies. Six of them provided theories about the technologies taught during the course. Five of them described the course via the forms of conducted exercises. Four of them comprised only keywords of the topics covered in the course. These fundamental results show how difficult it is to automatically extract questions that may help assess the level of users' competencies. Without a supervised model, for example, it would be easy to get a vast number of questions asking for the contact email of the teacher providing the course or on which days of the week someone can learn about JavaScript. These questions, however, are unsuitable for the assessment of a user's competencies.

To look for further possibilities to automatically extract questions that can help to assess the competency level of users, we used the script and methods defined in [33] in the first chapter of the following books [30–32]. We extracted 71 questions along with their corresponding answers (both of them in German, translated by the authors). Two examples of a question and answer pair are illustrated below:

Example 1:

Question: What are mnemonics?

Answer: To simplify the effort of writing directly in machine language, so-called assembler languages appeared from the 1940s onward. Assembler languages represent machine code in a readable form. For the (manageably) numerous machine commands, short English-like commands (so-called mnemonics) were created, which can be translated into machine code with one-to-one correspondence.

Example 2:

Question: What are tags in HTML?

Answer: Tags are symbols that mark the beginning and the end of an HTML element.

Despite minor language errors, the question and answer pairs represent the contained concepts reasonably well. Therefore, this first exploration seems to be a promising approach that is worth further investigation and assessment in a greater scope.

RQ3: To address the third research question concerning the use of Chatbots for lifelong learning counseling, we first developed an exploratory online survey comprising five questions. Most of the 89 respondents were university students. Not all participants replied to all questions. In the following, we will highlight the main results.

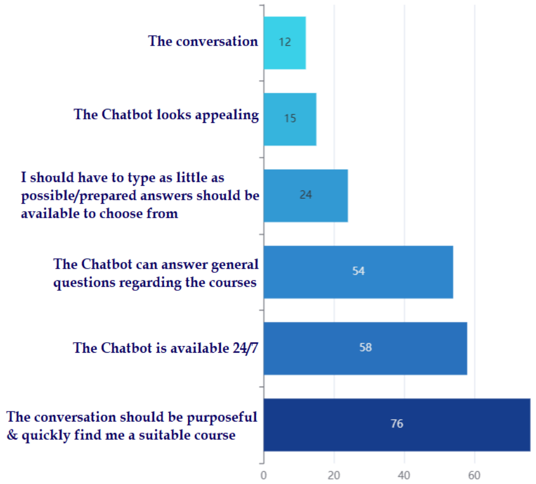

Fig. 3. Assuming you could use a Chatbot to find a suitable course, which features would be important to you? (multiple choice question, n=89).

Fig. 3 shows the results regarding the features of the Chatbot that are important to potential users. 76 of the 89 participants (85%) opted for a goal-oriented conversation that should quickly yield a suitable course. In addition, 58 out of 89 participants (65%) selected that a Chatbot should be accessible at any time so that the users are not limited in terms of time. Another important criterion worth mentioning is that a Chatbot should be able to answer general questions about the recommended courses, such as the place, price, duration, and time of the course. This option was selected by 54 out of 89 participants (60%). What is particularly striking is that few participants chose the appealing User Interface (15 of 89 participants, 16%) or having an engaging/stirring conversation (12 of 89 participants, 13%) as criteria.

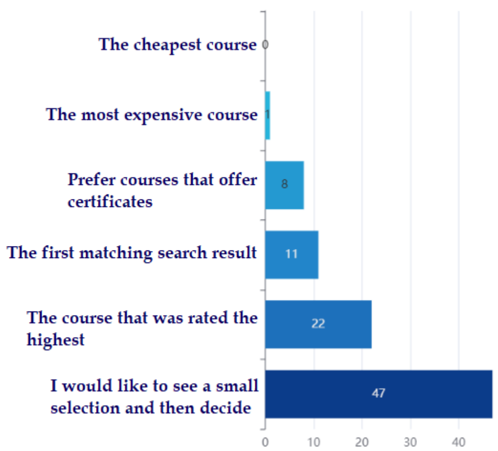

Fig. 4. Which courses should the Chatbot display to you? (Single choice question, n=89).

The responses to the question "Which courses should the Chatbot display to you?" are summarized in Fig. 4. Most participants (47 out of 89 participants, 53%) prefer to see a small selection of potentially relevant courses and then decide on a course. The answers also indicate that fewer participants are interested in courses that are rated high by others (22 out of 89 participants, 25%).

Another aspect worth mentioning is that only 8 of the 89 participants (9%) prefer to select courses offering certificates of attendance or successful completion. The price of a course, however, does not seem to be an important selection criterion, as only one of the participants selected this option. In addition, none of the participants showed interest in the cheapest course.

Fig. 5 shows the responses to the question regarding the data respondents are willing to share with a Chatbot. 73 out of 89 participants (82%) only want to share personal data that is relevant to the course search. The remaining 16 participants (18%), however, are open to sharing their personal data for a better user experience.

To dig deeper into the characteristics of a Chatbot providing counseling during lifelong learning course selection, we utilized the conducted *Chatbot workshop* with 15 experts in the field of technology-enhanced learning. In groups of five, participants were asked to design a flowchart for a Chatbot that would help them find valuable courses for lifelong learning. As a result, all three groups developed a basic interaction flow with the Chatbot to help them find suitable courses based on their desires and competencies.

Group one proposed a Chatbot for a system that has access to the user profile (e.g., educational background, skills), where the Chatbot is helping people in changing their job and/or improving or teaching new skills. The Chatbot analyzes the user profile data and depicts what the user is good at and what is missing. Then the Chatbot offers a selection of training/courses based on the user's interests and profile information.

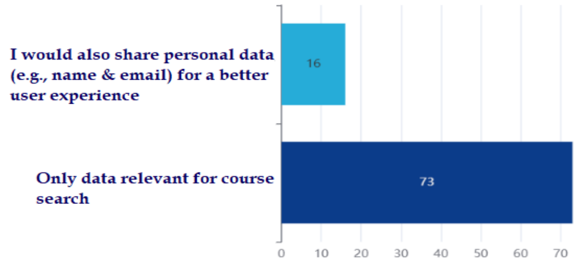

Fig. 5. What data are you willing to share with a Chatbot? (Single choice question, n=89).

Group two suggested a Chatbot named "Learning Companion". In this case, the Chatbot is supposed to help the user plan their learning, make suggestions based on their profile, and provide some effective support.

Group three designed a Chatbot that asked the users a few questions regarding their non-cognitive skills and the technologies they know. After the user answers the questions, the Chatbot recommends a course and asks the user if the user is interested in the course or not. If this is not the case, the Chatbot shows another course until the user is interested in a course. After this section, the Chatbot lists all the similar courses.

V. Discussion

To answer our first RQ, what user profile characteristics can be used in the context of LA instruments to help find suitable courses, our results show that profiles should reveal the user's competency levels. Another important attribute in the profiles is the desired career path of the user. By knowing the current competencies of the user and their desired career path, it is possible to offer visualizations showing how the user matches with their desired path. Moreover, it enables a system to suggest courses that can guide users toward their desired path. Experts in our study suggested providing these visualizations in the form of a spider chart, which in LA studies have been shown to support learners by illustrating their current learning progress and motivating them to learn and master new skills [16, 35].

When looking at available open options, such as Europass, to evaluate the utilization of user profiles, we concluded that the information in Europass only allows the inference of language-related competencies. Therefore, we do not consider Europass suitable for this purpose. Without additional information about the provided information within the CVs, a useful automatic application is not feasible. However, we think that having a digital platform is a good starting point to enable the collection of suitable information.

An important aspect to provide counseling regarding the course selection process of lifelong learners is to identify their current competencies. We argue that one way to achieve this is through some type of competency assessment. Manually creating assessment questions for all possible course topics is not feasible. Accordingly, RQ2 concerns the automatic extraction of questions that can help with a light assessment of users' competencies. Results from our consultations show that automatically extracting useful questions from the course descriptions within the portals is not feasible, mainly because the information contained in these descriptions is highly heterogeneous and in many cases not related to the content or competencies targeted by the courses. However, we saw that, in the specific case of "JavaScript", it is possible to automatically extract good enough questions by using the content of textbooks about the topic. As a limitation, we need to explore to what extent the NLP techniques used can work for other course topics. Nonetheless, the obtained results are promising.

To answer our third RQ, we investigated the relevant characteristics of Chatbots to provide counseling for learners during the course selection process. Our results from the online survey revealed that the Chatbot's conversation should be concise and quickly recommend a suitable course. The Chatbot should be intelligent enough to answer basic questions regarding the course, and it must be available 24/7. The user craves the usability of the Chatbot instead of the appealing user interface, which is a secondary preference. Our results further reveal that course prices seem less relevant, which is possibly due to the group of survey participants. However, a more in-depth survey is needed with a wide variety of participants (students, experts, researchers, and teachers) to validate the outcomes presented in this study.

As identified by our survey participants, a preselection of courses is essential. Nonetheless, more research is required on how to accomplish that. Even in Germany, people seem to be willing to share data that is relevant for a successful course search. A more in-depth investigation is needed to identify (data-saving) information for good search results.

The *Chatbot workshop* with experts confirmed our intuition that Chatbots are a good tool to assess the competency level of users and hence serve in the counseling aspect of searching for lifelong learning courses. Moreover, they seem to be a suitable user interface to provide this counseling by helping people to find suitable courses.

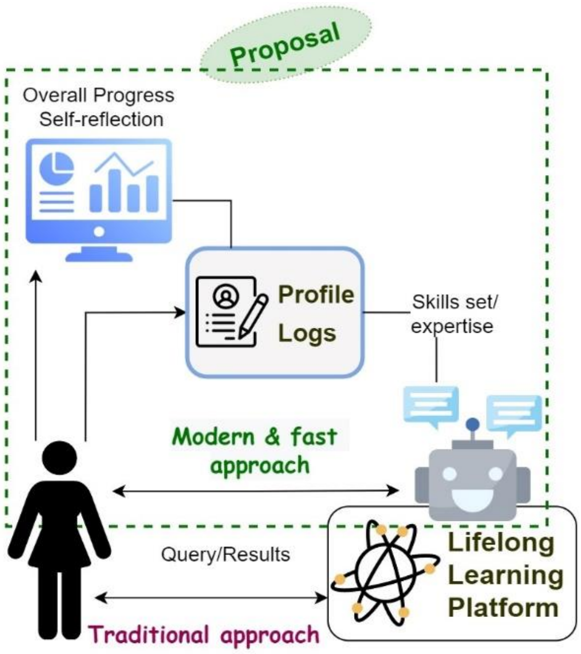

Fig. 6. The proposed structure extends the existing lifelong learning platform with digital counseling.

By examining the answers to our research questions, we derive the following design for the development of a lifelong learning counseling system designed to enhance current Lifelong Learning platforms. Fig. 6 shows a sketch of our design. It includes a user profile that stores the competencies of the user and also enables users to select the desired career path. The profile can then visualize the strengths and weaknesses of the user and overlay a projection on how these important attributes of the user will change by taking different courses. The whole counseling process can be moderated through the use of a Chatbot. The Chatbot can dig deeper into the competency level of the user through the use of assessment questions that can be automatically extracted from textbooks via NLP. Finally, suitable courses can be recommended to users.

VI. Conclusion

This paper presents a crucial first step in the iterative design-based research process aimed at developing lifelong learning platforms that are enhanced through digital counseling. It describes a set of formative studies that first allowed us to extract basic requirements for our proposed digital counseling. Moreover, the studies allowed us to examine the feasibility of using current technologies to develop the proposed digital counseling.

Based on the results from our studies, we consider that the implementation of the proposed design is feasible with current technologies. It will be an improvement to current lifelong learning platforms where users want to find suitable courses for them through the use of queries. The challenge is that in many cases users search for topics that they are not even familiar with and whose keywords they do not even know. We plan to implement the proposed structure by starting with the Chatbot as one of the key components, as the results indicate. Building upon this, additional evaluation and light assessments will be included. This will help lifelong learners to navigate the maze of lifelong learning course catalogs leading them to their desired career path.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Atezaz Ahmad conducted the study on finding LA user-profile characteristics that answers our first RQ. Jan Schneider conducted a study on using NLP to extract questions from the text that answers our second RQ. Daniel Schiffner was responsible for leading a survey on finding relevant characteristics of Chatbots that answers our third RQ. Natalie Kiesler helped in analyzing the data. Sebastian Wollny helped in the brainstorming and in preparing the RQs. Atezaz Ahmad wrote the paper, where all the authors contributed equally in further extending/rewriting the sections and preparing/proofreading the final version. All authors approved the final version.

Funding

This work was supported by DIPF | Leibniz Institute for Research and Information in Education, Germany. Caught In The Lifelong Learning Maze: Helping People With Learning Analytics And Chatbots To Find Personal Career Paths.

References

[1] M. London, *The Oxford Handbook of Lifelong Learning*, Oxford University Press, 2011.
[2] D. Antoci, “Encarta,” *Lifelong Learning*, 2022.
[3] H. Ates and K. Alsal, “The importance of lifelong learning has been increasing,” *Procedia-Social and Behavioral Sciences*, vol. 46, pp. 4092–4096, 2012.
[4] K. Głabicka, “The importance of lifelong learning in XXI century,” *Central European Review of Economics & Finance*, vol. 8, no. 2, pp. 51–61, 2015.
[5] A. H. Odeh *et al.*, “Analytical and comparison study of main web programming languages — ASP and PHP,” *TEM Journal*, vol. 8, no. 4, pp. 1517–1522, 2019.
[6] P. Chakraborty, R. Shahriyar, A. Iqbal, and G. Uddin, “How do developers discuss and support new programming languages in technical Q&A site? An empirical study of Go, Swift, and Rust in Stack Overflow,” *Inf Softw Technol*, vol. 137, p. 106603, 2021.
[7] IWWB. *(InfoWeb Further Education): About IWWB*. [Online]. Available: https://www.iwwb.de/kurssuche/startseite.html
[8] H. Weiterbildungsdatenbank. (Aug. 29, 2022). Education-portal-hesse: About education-portal-hesse. [Online]. Available: https://www.bildungsportal-hessen.de/g10341
[9] Weiterbildung.de. (Aug. 29, 2022). Further education: about further education. [Online]. Available: https://www.weiterbildung.de/ueber-uns

[10] S. Zolaktaf and G. C. Murphy, "What to learn next: Recommending commands in a feature-rich environment," in *Proc. 2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA)*, 2015, pp. 1038–1044.

[11] F. E. Weinert, "Concept of competence: A conceptual clarification," 2001.

[12] S.-C. Wong, "Competency definitions, development and assessment: A brief review," *International Journal of Academic Research in Progressive Education and Development*, vol. 9, no. 3, pp. 95–114, 2020.

[13] G. Siemens, "Call for papers of the 1st international conference on learning analytics & knowledge (lak 2011)," 2010.

[14] S. J. Aguilar, S. A. Karabenick, S. D. Teasley, and C. Baek, "Associations between learning analytics dashboard exposure and motivation and self-regulated learning," *Comput Educ*, vol. 162, p. 104085, 2021.

[15] I. Jivet, M. Scheffel, M. Schmitz, S. Robbers, M. Specht, and H. Drachsler, "From students with love: An empirical study on learner goals, self-regulated learning and sense-making of learning analytics in higher education," *Internet High Educ*, vol. 47, p. 100758, 2020.

[16] Y. Park and I.-H. Jo, "Development of the learning analytics dashboard to support students' learning performance," *Journal of Universal Computer Science*, vol. 21, no. 1, p. 110, 2015.

[17] S. Wollny, J. Schneider, D. Mitri, J. Weidlich, M. Rittberger, and H. Drachsler, "Are we there yet? — A systematic literature review on chatbots in education," *Front Artif Intell*, vol. 4, 2021.

[18] M. Prensky, "Khan academy," *Educational Technology*, vol. 51, no. 5, p. 64, 2011.

[19] J. Knox, S. Bayne, J. Ross, H. Macleod, and C. Sinclair, "MOOC pedagogy: The challenges of developing for Coursera," *Association for Learning Technology (ALT) Online Newsletter*, no. 28, 2012.

[20] Iversity. Iversity: About Iversity. [Online]. Available: https://iversity.org/

[21] FutureLearn. FutureLearn: About FutureLearn. [Online]. Available: https://www.futurelearn.com/about-futurelearn

[22] M. R. Kennedy, "LinkedIn learning product review," *Journal of the Canadian Health Libraries Association/Journal de l'Association des bibliothèques de la santé du Canada*, vol. 40, no. 3, pp. 142–143, 2019.

[23] P. Carvalho, "Academic MOOCS providers for learners vs instructors," in *Proc. EDULEARN21 Proceedings*, 2021, pp. 9447–9455.

[24] J. P. Espada, C. C. Rodr'iguez, V. Garc'ia-D'iaz, and R. G. Crespo, "Method for analysing the user experience in MOOC platforms," in *Proc. 2014 International Symposium on Computers in Education (SIIE)*, 2014, pp. 157–162.

[25] R. S. Adham and K. O. Lundqvist, "MOOCS as a method of distance education in the arab world — A review paper," *European Journal of Open, Distance and E-learning*, vol. 18, no. 1, pp. 123–139, 2015.

[26] F. Wang and M. J. Hannafin, "Design-based research and technology-enhanced learning environments," *Educational Technology Research and Development*, vol. 53, no. 4, pp. 5–23, 2005.

[27] GoogleDrawing. (Aug. 29, 2022). *Google Drawings.* [Online]. Available: https://docs.google.com/drawings

[28] A. Ahmad *et al.*, "What indicators can i serve you with? An evaluation of a research-driven learning analytics indicator repository," in *Proc. the 14th International Conference on Computer Supported Education - Volume 1: CSEDU*, 2022, pp. 58–68.

[29] Europass. Europass (free and personal tool for learning and working in Europe): About Europass. [Online]. Available: https://europa.eu/europass/en/about-europass

[30] J. L. Zuckarelli, "Wie stelle ich sicher, dass ich (und andere) mein Programm später noch verstehe?"*Programmieren lernen mit Python und JavaScript*, Springer, 2021, pp. 75–85.

[31] J. L. Zuckarelli, "Was muss ich tun, um ein Programm zum Laufen zu bringen?"*Programmieren lernen mit Python und JavaScript*, Springer, 2021, pp. 441–450.

[32] J. L. Zuckarelli, *Programmieren lernen mit Python und JavaScript: Eine praxisorientierte Einführung für Einsteiger*, Springer, 2021.

[33] T. Steuer, A. Filighera, and C. Rensing, "Exploring artificial jabbering for automatic text comprehension question generation," in *Proc. European Conference on Technology Enhanced Learning*, 2020, pp. 1–14.

[34] A. Ahmad *et al.*, "Connecting the dots — A literature review on learning analytics indicators from a learning design perspective," *J Comput Assist Learn*, 2022.

[35] J. Kim, I.-H. Jo, and Y. Park, "Effects of learning analytics dashboard: analyzing the relations among dashboard utilization, satisfaction, and learning achievement," *Asia Pacific Education Review*, vol. 17, no. 1, pp. 13–24, 2016.

Atezaz Ahmad is a research assistant and doctoral candidate within the Leibniz Institute for Educational Research and Information and Goethe University in Frankfurt am Main, Germany. His PhD thesis is about learning analytics indicators and dashboards, where he is working, developing and evaluating a LA tool called OpenLAIR that helps course designers, teachers, students, and educational researchers to make informed decisions about the selection of learning design activities, LA indicators, and metrics for their course design or LA dashboard. He is further working on NLP to automize the process of harvesting LA indicators and their metrics from the LA literature and uploading them to OpenLAIR to keep the tool up to date.

He graduated with a master's in software system engineering in learning analytics from RWTH Aachen University, Germany. His research interests are learning analytics indicators and dashboard, visual analytics, NLP, and text data mining.

Natalie Kiesler completed her doctorate in computer science at Goethe University Frankfurt, Germany in 2022. The focus of her thesis was on modeling competencies and tutoring feedback for novice learners of programming. She is currently a senior researcher at the DIPF Leibniz Institute for Educational Research and Information in Frankfurt, Germany where she contributes to the development of an open research data infrastructure for qualitative research data. Dr. Kiesler's research interests include computing education, competency-based learning and teaching, feedback, and open science.

Daniel Schiffner is the head of the Educational Computer Science group at the DIPF. After his studies in Computer Graphics, he received his PhD in 2012 at the Goethe University Frankfurt, Germany. He then began research in the field of usability and educational technologies. In 2014 he took the position of head of research and development at the central e-learning institution studiumdigitale at Goethe University. He switched to his current position in 2019, where he researches and maintains information platforms, usability of those as well as new technologies in the context of education.

Jan Schneider is a postdoctoral researcher at the Educational Computer Science group of the DIPF. He started his career as a researcher in 2008 working as a Human Computer Interaction researcher at the Expertise Centre for Digital Media at Hasselt University in Belgium. There he worked for several research projects in the areas of Multi-Touch and mobile interactions. On December 2017 he received his PhD from the Open University of the Netherlands on the topic of "Sensor based Learning support". During his PhD he worked on two European projects (Metalogue and Wekit) and his developed research prototypes got awarded in three different international conferences (EC-TEL 2014, EC-TEL 2015, ICMI 2015). Dr. Schneider's current research focus is in the area of Multimodal Learning Analytics (MMLA), where he is investigating the creation of generic frameworks and solutions designed to support the learning process with the use of multimodal data.

Sebastian Wollny is a PhD student at the DIPF Leibniz Institute for Research and Information in Education, based in Frankfurt am Main, Germany. Since his bachelor's degree in Electrical Engineering and Computer Science at the Multimedia Communications Lab of the TU Darmstadt, he has been working on the processing of information in learning environments. Sebastian focuses in his PhD on dialog-based learning, which a special focus on Chatbots in education, Natural Language Processing, and AI in education.