TOWARDS A USER FOCUSED DEVELOPMENT OF A DIGITAL STUDY ASSISTANT THROUGH A MIXED METHODS DESIGN

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ABSTRACT

Digital Study Assistants (DSA) aim to support individual learning processes by designing them appropriately and efficiently based on recommendations. In this paper we present a prototype of a DSA for students in higher education of three German universities. The digital data driven DSA is integrated into the local learning management system and consists of recommender modules with a certain kind of recommendation for a specific purpose, e.g., recommending Academic Contacts that fit an expressed academic interest. The modules implemented so far use a wide range of methods: Classic rule-based Artificial Intelligence (AI) or Neural Networks, that can detect complex features and patterns in large data sets. To evaluate the current prototype of the DSA we used a mixed methods design approach with concurrently collected user data and qualitative data. A first insight in the user data suggests that recommender modules providing personalized recommendations are more likely to be used by students. A focus group discussion with students confirmed these findings with the suggestion to make the DSA more personal, individual, interactive, supportive, and user-friendly. In conclusion we present ideas for the further development of the prototype based on these findings.

KEYWORDS

AI in Education, Digital Study Assistant (DSA), Higher Education, Individual Learning Process, Innovative Learning Management Systems (LMS), Mixed Methods Design, Recommender Systems

1. INTRODUCTION

In the digital age learners are confronted with an overwhelmingly rich supply of educational resources of various qualities (Atenas *et al.*, 2014), but limited temporal and attentional processing capabilities (Sweller, 1988). In contrast to former times, when access to information and education was a privilege, nowadays the choice of the right learning resource at the right time has become a key aspect of successful education.

Digital Study Assistants (DSA) have the potential to support individual learning processes by designing them appropriately and efficiently. They can preprocess large databases containing educational resources and recommend those fitting the individual needs of the user by leveraging AI technology (Alexander *et al.*, 2019).

Although self-regulated learning (Zimmerman, 1990) in higher education plays an important role in the demand for lifelong learning, studies show mixed results when it comes to integrating technology into the learning process (Broadbent and Poon, 2015). Students can benefit from elaborating on and developing personal educational goals (Morisano, 2013; Schippers *et al.*, 2020) and it has been argued that self-regulated learning relies on goals (Zimmerman, 1990; Virtanen et al., 2013) Digital assistants can remind and nudge learners to keep them on track towards their self-set educational goals, even in face of distractions.

Learning partnerships or learning groups of students can amplify learning processes (Okita, 2012). Digital assistants can find peers with similar educational interests, based on data patterns, and provide contact recommendations to students. In the context of higher education, digital assistants can guide students to plan, follow their plan and reflect upon learning behaviors and potential improvements. In these ways digital assistants can serve as amplifiers of learning processes.

1.1 Study Assistant Software Prototype used in our Field Study

We have developed a digital data-driven study-assistant, which is integrated into the local learning management system (LMS) Stud.IP of three German universities. Connecting the DSA software to an established LMS provides students with easy access to the assistant and its features. Simultaneously, attaching the DSA to the LMS allows for an aggregation of information of a university's educational resources such as courses, study programs and user relations, by obtaining information from its LMS database.

Students interact with the service through the learning management system *Stud.IP* (Stockmann and Berg, 2005). The main frontend of our study assistant is implemented as a plugin for the LMS. The job of the frontend is exclusively to visualize data provided by the backend and to react to user-inputs. The frontend can interact with services of the user's university, such as collecting data from the Stud.IP database to and send it to the backend. As the Stud.IP system allows to regularly execute jobs on its servers, the frontend can additionally serve as a data collection interface for courses, dates of scientific talks, and other information added by lecturers and students. Backend and frontend communicate via a RESTful interface using textual representations with a stateless protocol which allows to *receive, transfer, update* or *delete* data through *requests* formatted following the JSON-API standard. Especially when web services dealing with personal data are concerned, adhering to high security standards is mandatory. The data we transfer over the internet is pseudonymized, transferred over encrypted channels, and *salted* (Morris and Thompson, 1979). Furthermore, the backend does not communicate with requests other than the respective instance of the frontend. The core of our architecture resides on the backend server, written in *python3* and based on the Django ("Django", 2020) framework and runs a PostgreSQL database (Stonebraker and Kemnitz, 1991).

1.2 Modular Software Architecture with Recommender Modules

The current software prototype is the third version in a row of annual releases with a growing set of functionalities. These functionalities are encapsulated into so-called *recommender modules*, each presenting contextual information for a specific topic.

Recommender modules are always defined from the user perspective: They provide a certain kind of recommendation for a specific topic, e.g., recommending academic contacts that fit to an expressed academic interest. The modules implemented so far use a wide range of methods: Classic rule-based Artificial Intelligence, often used in expert systems, combines known facts about the world with rules about these facts to derive new potentially useful knowledge, while modern approaches of AI, such as Neural Networks, can detect complex features and patterns in large data sets.

Following object-oriented software design patterns, this design allows to develop separate functionalities and to test, evaluate and improve them independently. The designed recommender modules offer recommendations to optimize their study organization (e.g., information on studying abroad, information on funding). But also, students can learn more about the role of the memory function in learning processes and receive personalized recommendations for optimizing their learning behavior or can inform themselves about techniques for self-regulated learning. Currently the following recommender modules have been implemented, used, and tested by university students in an ongoing field study:

Academic Interests: An AI-based semantic search engine relating natural language inputs with a knowledge domain and suggesting educational resources, e.g., suggestions for courses, based on their content.

To-do: A list of tasks the user formulates in natural language.

Scientific Career: This module gives hints towards funding, external sources of information in the web and events, institutions, and courses within the local university, directed towards a scientific career.

Data Ethics: This module provides learning content about data-ethical questions related to digital assistants.

Personality Module: Long-term memory, short-term memory and the ability for task-switching are measured with psychometric measures. Based on the results students get recommendations for their learning behavior.

Learning Organization: A list of methods to inform about techniques for self-regulated learning.

Open Educational Resources: A general introduction in the field of open educational resources (OER) and a list of OER depositories.

Funding: A step by step guide giving tips for multiple approaches towards financing oneself during one's studies.

Evaluation: A questionnaire asking the users to rate their experience with the DSA.

Academic contacts: This recommender module offers students the possibility to find other learners at the three partner universities that share adjustable properties, such as common interests, study program, degree or a common destination country for a semester abroad.

The goal of this study is to derive requirements for enhancement for a current DSA system through quantitative and qualitative methods. These requirements ought to cover suggestions for individual recommender modules as well as general aspects of the DSA.

2. METHODS

To evaluate the current prototype of the DSA we used a mixed methods design approach (Schoonenboom and Johnson, 2017) with concurrently collected quantitative and qualitative data from the current field study, running since December 2020 at three universities in Northern Germany.

2.1 Quantitative: Data Collection, Data Set and Data Analysis

To evaluate the user interactions with the DSA we used data from the PostgreSQL database of the backend server, generated between December 2020 and May 2021. The resulting adjusted data set includes information about interaction of users with recommender modules, the evaluation of the single activities in the recommender modules, the university of origin, the user target degrees, the subjects of study and the current semester of the enrollment. We use descriptive statistics to give a first insight in the interaction of the users with the recommender modules. It is important to note that albeit originating from the same data, our analyzing methods highlight different perspectives on this data. These perspectives are dependent on how much data users donated. This means that while some, more general statistics can be generated from the entire data set, other statistics rely on more specific data that not all or only few participants shared with the DSA.

2.2 Qualitative: Design Thinking Workshop

For the purpose of iteratively evaluating the prototype, a total of four virtual focus group discussions were held in March 2021 in a design thinking workshop format (Plattner et al., 2010) with seven to nine students from each of the three university locations involved. The primary compilation criterion of the groups was the study phases, which were subdivided into introductory phase, middle study phase, and study completion phase.

The overall goal of these discussions was to evaluate the status of the prototype for the purpose of gathering suggestions for optimization.

To evaluate the current state of the prototype, the students were divided into small groups in which they selected two to three recommender modules and tested them together. Finally, the group was asked to complete an online questionnaire, tailored to the respective recommender module. The entire group then collected suggestions for optimizing the individual recommender module and the DSA in general.

3. RESULTS

We present the results from the quantitative method based on data from the DSA’s backend followed by the results from the qualitative method based on a design thinking workshop.

3.1 Quantitative Data Analysis Results

The latest developed prototype is used by Bachelor and Master students of various study programs of three German universities. From December 2020 till the mid of May 2021 the DSA had 688 active users from all three partner universities with more than 40.000 single interactions with different recommender modules.

When a student interacts with the DSA the first time, all recommender modules are presented with a short teaser prompt. Students can then choose which recommender modules they want to explore and use further. Students can either choose to activate recommender modules, to deactivate them or to not interact with them at all. Figure 1 shows the usage decisions per recommender module. The *OER*-module is activated by the most users, followed by the *Academic Interests*, *Personality* and *Learning Organization Modules*.

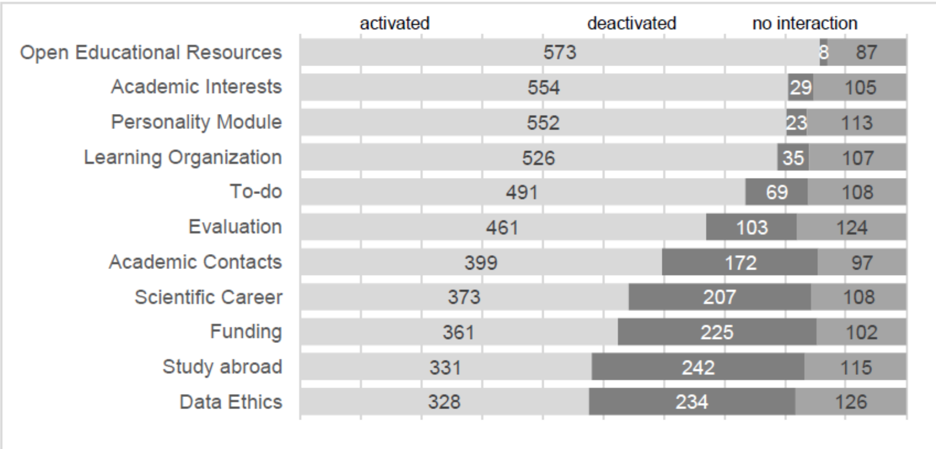

Figure 1. Usage per recommender module for N = 688 users. The numbers in the colored areas represent the amount of interaction decisions made by users where the first number represents recommender module activation, the second number deactivation and the third number inaction

Conversely, the deactivation rate follows a trend inverting activation rate per recommender: While the *OER* recommender module was seldomly deactivated, 34% of users deactivated the *Data Ethics* recom-mender module. With an average of 108, non-interactions stay relatively uniform between recommenders.

User data, such as their semester of enrollment and their degree are visualized in figure 2. As a comparison, we also included the number of PhD students ("Promotion") and an excerpt of students with enrollment in non-Bachelor and non-Master studies ("Magister"). The data presented in figure 2 shows that most users study in a Bachelor's program. When it comes to the semester of enrollment, most users within a Bachelor's or Master's program are first semester students. This is followed by students in their third semester.

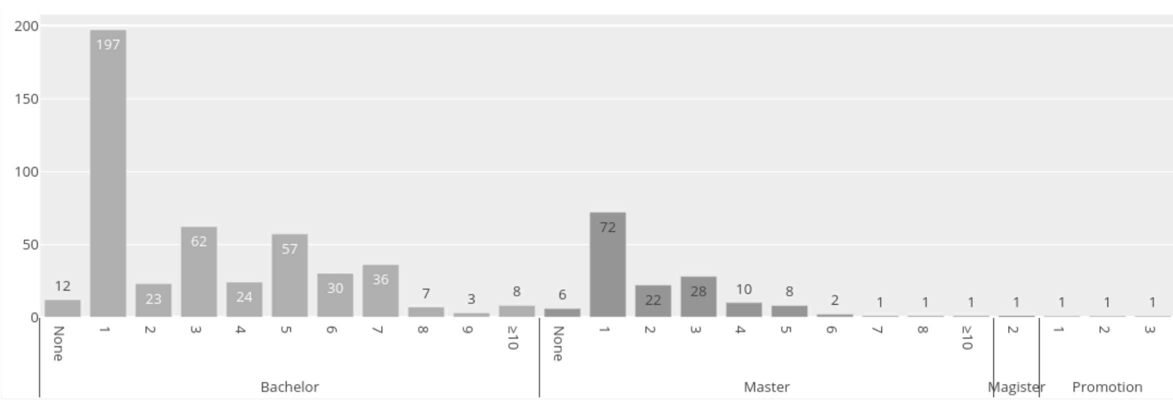

Figure 2. User target degrees and usage of recommender modules (N = 614)

To further analyze the recommender usage in relation to degree, we analyze the recommender interaction frequency of 458 Bachelor and 151 Master students. This leads to a total of 609 users. We investigate whether there are differences in recommender module usage frequency between users enrolled in their Bachelor and Master studies respectively. We present the results in table 1.

Table 1. Comparison of relative usage between Bachelor and Master degree

Recommender Module	Relative usage Bachelor	Relative usage Master	Difference in relative usage frequency
Academic Interests	82.3	80.8	1.5
To-do	75.9	63.6	12.3
Scientific Career	55.5	54.3	1.2
Data Ethics	48.3	45.0	3.3
Personality Module	82.9	76.8	6.1
Learning Organization	80.3	72.8	7.5
Open Educational Resources	87.1	85.5	1.6
Funding	64.2	44.4	19.8
Evaluation	71.4	60.9	10.5
Academic Contacts	60.9	58.2	2.7
Study Abroad	53.0	35.7	14.3

Investigating the difference between relative usage by Bachelor and Master students, there is a >10% difference between relative recommender usage in the *To-do, Funding, Evaluation* and *Study Abroad* recommenders. All these recommenders are used relatively more frequently by Bachelor students than by Master students.

3.2 Qualitative Results: Design Thinking Workshop

During the *design thinking workshops*, students were asked to select two to three recommender modules and test them, as indicated above. Table 2 illustrates which recommender modules were tested to what extent.

Table 2. Recommender module-Ranking of the Design Thinking Workshops

Recommender Module	*n*
Personality Module	7
Academic Contacts	7
Academic Interests	4
Learning Organization	4
Study Abroad	3
To-do	2
Scientific Career	2
Data Ethics	1

To assess the current state of each tested recommender module, following the group work, students were asked to rank their impressions for each recommender module in a four-dimension matrix with the attributes very/not helpful and very/not comprehensible. The results show that the recommender modules *Personality Module* and *Academic Contacts* were used most frequently.

With regard to the latter, it was suggested that more transparency of the assigned matches should be established so that more information on each match is shown in advance.

The students also recognize great potential in the *Personality Module*. In particular, students in the introductory phase expressed great interest in this recommender module. In order to optimize this module, it was suggested that individual input be taken into account and to shape the recommender module in a more personal way.

The students also see great potential in the AI-supported module *Academic Interests*. The most common feedback in this area was that it is unclear how to formulate academic interests. Specific suggestions from the students were to raise students' awareness of how to formulate and pursue individual educational goals. In keeping with one of the DSA's goal dimensions of initiating student self-reflection, questions should help students reflect on various aspects of their own studies to derive specific learning goals. This reflection process should be stimulated by reflective questions.

In this sense, students should receive sample input for the formulation of study interests. For this purpose, examples could appear that have been entered by other students.

These results can be linked to the general suggestions for improvement: Within the framework of a structuring qualitative content analysis according to Kuckartz, (2018), five categories were developed inductively, from which the following attributes students ask from a DSA, result: *personal*, *individual interactive*, *supportive* and *user-friendly*.

4. DISCUSSION

In this section, we interpret the results presented in section three and derive future development requirements from them.

4.1 Interpretation of the Results

Investigating the usage decisions per recommender, a clear hierarchy in recommender preference can be derived. Generally, the number of non-interactions with recommender modules is relatively uniform across recommenders. This indicates that recommenders were explored evenly across users.

The *OER* recommender was used almost universally among all users. This is followed by the *Academic Interests*, *Personality Module* and *To-Do* recommenders with less than one hundred deactivations. The high number of activations of these recommenders suggests that students were particularly interested in the domain of service these recommenders reside in. For the Personality Module recommender, this is reflected in the number of selections of recommenders students were interested in during the design thinking workshop, with seven students selecting this recommender for exploration. The low number of deactivations of these recommenders conversely indicates that students did at least deem these recommenders useful enough to keep them in their activated recommenders list. In contrast, the *Academic Contacts*, *Scientific Career*, *Funding*, *Study Abroad* and *Data Ethics* recommenders all were activated by less than 400 users and, save of *Academic Contacts*, were deactivated by over 200 users. This indicates that these recommenders were not deemed to be as useful or relevant as the aforementioned recommender modules. Even though the *evaluation* recommender was deactivated by 103 users, a non-trivial number of 461 users activated this recommender module. Because this recommender module serves the sole purpose to collect more detailed feedback from users, it can be assumed that the general level of readiness of users to help improve the DSA through feedback is elevated. In the light of the data presented here being collected from users that agree for a data donation, this result is to be expected.

When it comes to DSA use per degree and semester, our results show that there is a higher number of users in their Bachelor studies compared to users in their Master studies. Again, this mismatch is to be expected assuming a distribution of users in terms of degree as there are more Bachelor students enrolled at German universities compared to Master students. Additionally, our data shows that most users are enrolled in early semesters, regardless of degree, implying that students in higher semesters found the DSA as a whole to be of less interest for them compared to students in earlier semesters.

Comparing relative use between Bachelor and Master students, we observed a difference of 10% or more in four of eleven recommenders: *To-Do*, *Funding*, *Evaluation* and *Semester Abroad* recommenders were less frequently activated by Master students compared to Bachelor students. It has to be noted that with N=458 for Bachelor students and N=151 for Master students, this discrepancy in activated recommenders may very well be the result of sampling from populations with different sizes. In the case of the *To-Do* and *Funding* recommenders, we interpret these results to originate from a generally higher proficiency of Master students to organize their studies and their finances during studying. Because Master students were able to build these skills during their Bachelor studies already, the *To-Do* and *Funding* recommender modules are hence of less interest for them. This hypothesis is further strengthened by the fact that the *Learning Organization* recommender module which also focuses on organizing one’s studies, is also activated less by Master students compared to Bachelor students (7.5%). Regarding the *Semester Abroad* recommender module, we hypothesize that the divergence between Master and Bachelor student use originates from the circumstance that Master students may have already completed their studies abroad in their Bachelor studies.

Students participating in the design thinking workshop expressed a high interest in the *Academic Contacts* recommender. In parallel, students reported to be especially interested in the *Personality Module* recommender, emphasizing that their user experience was only held back by the lack of transparency of how matches were generated.

Students additionally reported a high degree of helpfulness and comprehensibility of the *Academic Interests* recommender.

4.2 Limitations

A general limitation of the findings from the quantitative approach presented in this work is the inconsistency between sample sets between analysis approaches: Because our analysis methods focus on different properties of users and their interaction with the DSA, insights derived from one method are not necessarily generalizable to all users, but only describe the user experiences of one subset of users. This under sampling of the total underlying user data is a result of the DSA's design regarding data protection and the subsequent possibility of users to carefully select data they want to share with the system. Albeit this design being in line with possible data-protection goals, it also hinders a thorough analysis of usability through quantitative means.

Additional limitations of our findings are related to the *user interface* of the DSA. The order in which the recommender modules are represented for the user may influence their interaction with the recommender modules and their preferences. The latter is especially obvious for the *OER* module. One explanation might be the fact that in the workshops, students were informed during the module presentation that only the concept of *OER* is presented in this module, but that there are no learning materials to be found. One assumption is that students were not aware of this when activating the DSA recommender module, and that the large number of activations can be explained by the fact that students initially assumed that they would find helpful learning material there.

4.3 Future Development

Regarding future development we derive three factors from general recommender usage: firstly, the frequently activated recommender modules *OER*, *Academic Interests*, *Personality Module* and *To-Do* already cover topics of interest for users. These recommenders therefore should be extended in their functionality. Conversely, the often-deactivated recommenders *Academic Contacts*, *Scientific Career*, *Funding*, *Study Abroad* and *Data Ethics* need to be enhanced in their usefulness or evaluated to be removed from the DSA. Because no recommender stands out in terms of non-interaction, we conclude that all recommenders are at least of initial interest for students and therefore, no recommender should be removed on the basis of not being of any initial interest to users.

The semester of enrollment per user shows that most users are in their first semesters. This suggests that the DSA is of primary interest for students in their initial study stages. One future development goal therefore should be to make recommenders more useful for students in low semesters. In parallel, future developments should also focus on identifying, designing, and implementing more useful recommender modules for students of higher semesters, as they are less present in our user data. A recommender module for finalizing a study program and writing a thesis could be a prospective candidate. A similar picture forms regarding the relationship between users and their degrees: Bachelor students are already engaged with the DSA and therefore should be considered as main users. Conversely, Master students are not as engaged with the DSA and therefore new recommenders tending to Master student's wishes should be designed or existing recommenders should be modified to account for them.

As *OER*, *Personality Module* and *Academic Interests* recommender modules already enjoy a high degree of engagement and should be focused on for improvement in future development endeavors. Regarding the recommender module *Academic Contacts*, there is a particular need for optimization in the range of usability. Here, the non-transparency of the matches and the anonymity were criticized during the design thinking workshop. Based on these findings, the creation of personal cards is planned for the further development of this module. In this way, depending on the data students share with other users, they will receive more information about their matches. In addition, the matching function will relate multiple search requests. For example, it will distinguish either by similarity or by complementarity.

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