Proceedings of the 19th Conference on Computer Science and Intelligence Systems (FedCSIS) pp. 253–258 DOI: 10.15439/2024F2707 ISSN 2300-5963 ACSIS, Vol. 39

Successfully Improving the User Experience of an Artificial Intelligence System

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***Abstract*—An important aspect of Artificial Intelligence (AI) Systems is their User Experience (UX), which can impact the user's trust in the AI system. However, UX has not yet been in the focus of AI research. In previous research, we have evaluated the UX of the Meta AutoML platform OMA-ML, uncovering weak points and proposing several recommendations for ensuring a positive UX in AI systems. In this paper we show that implementing those recommendations leads to measurable UX improvements. We present the UX-improving features implemented in a new release of OMA-ML and the results from a second UX evaluation. The UX of OMA-ML could successfully be improved in four interactive principles (suitability for the user's tasks, self-descriptiveness, user engagement and learnability). We argue that an iterative approach to UX potentially leads to more human-centered AI.**

I. Introduction

ARTIFICIAL INTELLIGENCE (AI) SYSTEMS are programs or machines that can mimic human cognitive behaviour [1]. AI systems, in particular ones using Machine Learning (ML), are present in our everyday use, e.g. facial recognition in smartphones [2] or translation tools using natural language processing (NLP) [3]. An important aspect of AI systems is their User Experience (UX). UX in the context of AI systems assesses a user's overall experience with the AI system [4]. Understanding the user's needs and behaviours is necessary, as a bad UX may contribute to an AI system's failure [5]. While the UX is an important aspect of an AI system, there is limited discussion about it in the AI community.

We discussed this in previous research [6], and aimed to raise awareness by using the case study for the AI platform OMA-ML[1] (Ontology-based Meta AutoML) [7][8]. Based on the case study, 104 UX issues were found, categorised and resolved. Additionally, we proposed 12 measures and 4 recommendations to ensure a positive UX for AI systems. Based on the same Methodology [6], the interaction of 29 participants using the updated version of OMA-ML was evaluated.

In this paper we show that implementing those recommendations leads to measurable UX improvements. We present the results from the new case study and the UX improvements implemented in a new release of OMA-ML. Based on the ISO 9241-110[2] interaction principles, OMA-ML could improve in the interaction principles: suitability for the user's tasks, self-descriptiveness and user engagement compared to the previous evaluations weak points and even exceed in the learnability interaction principle beyond the target state. However, it has yet to reach the target states in all of them fully.

The remainder of this paper is structured as follows: Section II presents related works. In Section III, the UX evaluation methodology is discussed. Section IV lists the UX improvements made to OMA-ML. The results from the new UX evaluation are presented in Section V. Finally, Section VI concludes the paper and discusses future works.

II. Related Work

AI systems are gaining increasing importance, with new powerful AI applications being released regularly. Most recently, AI systems using Generative AI have gained prominence with applications such as ChatGPT [9], offering *human-like interactions* but also enabling new ways of powering AI systems such as code completion tools [10]. While the underlying AI algorithm is an important aspect of an AI system's success, it also depends on how it interacts with the user [11]. This is why UX is important, as it represents a collection of strategies for understanding a user's needs and behaviours with the system to create useful, stable systems and services [12].

However, in the past, the AI, UX and Human Computer Interaction (HCI) communities applied AI and specifically ML on a more technical approach for the creation of new methods to support the UX process itself [13] or the creation of new interfaces to interact with systems (e.g. voice interfaces) [14] [15]. The HCI research community also proposes guidelines for Human-AI Interactions [16]. In the AI community, a focus is emerging for a user-centred approach for AI systems. One prominent research area in AI that applies this is Explainable AI (XAI) [17]. XAI is a research field that emerged to focus on explaining the decision-making of AI models to the user [18] and providing insight into the data [19]. Understanding how a model came about a decision can increase usability and give the user confidence in the system, and usability is a critical part of the UX. Usability accesses how easy a user interface is to use and refers to methods for improving the ease of use during the system's design process [20]. Our previous work proposed a list of recommended measures to ensure a good

[1]https://github.com/hochschule-darmstadt/MetaAutoML
[2]https://www.iso.org/obp/ui/#iso:std:iso:9241:-110:ed-2:v1:en

UX for AI systems [6]. These recommendations are based on the interaction principles formulated in ISO 9241-110:2020[3] and the results from the usability study of OMA-ML. The UX methodology used for this study is introduced in the next section.

III. Methodology

Evaluating the usability of an AI platform can be a three-stage process. First, a *Use Case Model* [21] is developed to set the scope of the UX research. The use cases are extracted from the user interaction concept for this research. Next, an *Expert Review* is conducted. During the Expert Review, a UX expert inspects a system to uncover usability issues. Expert Reviews assess the design by heuristics and guidelines or principles [22]. An important set of guidelines to assess usability is the ISO Standard 9241-110:2020[4], specifically the 7 outlined interaction principles: suitability for the user's tasks, self-descriptiveness, conformity with user expectations, learnability, controllability, use error robustness, user engagement. These interaction principles are used to measure the AI platform's usability. Based on the Use Case Model, the UX expert determines the target state for each interaction principle. The interaction principles are measured on a scale of 1 to 5 [6]. The UX Expert then evaluates the AI platform to uncover usability issues and rate the AI platform's actual state for each interaction principle. To rate the state, the German ISO 9241-110 [23] provides a checklist to determine whether the interaction principle requirements have been met. Expert Review is an effective method for catching issues. However, it may miss domain-specific issues or needs that would otherwise be found by the target audience [22]. This is revolved by performing a usability study. For this study, qualitative research techniques were chosen to comprehend what the users value the most in their experiences [24]. In the first usability study, a total of 8 usability tests were performed. Each Usability test consisted of *pretesting questions*, *follow-up questions* and *post-testing questions*. During the pretesting questions, general information about the participants was gathered, such as their demographics, motives, beliefs, expectations, existing approaches and prior experiences with AI platforms. Afterwards, the participants were given tasks they had to resolve using the AI platform. During this, follow-up questions were asked to uncover the motivations and expectations of their behaviour with the platform. During the interaction with the platform, the participants were invited to think aloud, sharing their way of thinking. Finally, after completing the work tasks, the participants were asked post-testing questions. These questions aimed to gather their feedback on the overall user experience (For a more in-depth explanation of the used usability study process, see [6]). Throughout the usability test, usability issues were collected from the participants and compiled into a list containing 104 UX issues. Each issue was categorised by the interaction principle that it infringes and given a severity rating. This severity indicates how urgently the issue must be addressed. It is based on the five severity levels by Nielsen Norman Group [25] (0: not a usability problem, 1: cosmetic problem, 2: minor usability problem, 3: major usability problem, 4: usability catastrophe). Afterwards, OMA-ML was updated resolving each UX issue. The major UX improvements are introduced in the next section.

Finally, the entire UX evaluation was repeated with the updated version of OMA-ML and the same methodology. First, an Expert Review was conducted, collecting new issues and determining the usability state of the updated OMA-ML platform. The new state was compared to the target state and the baseline, which are the first Expert Review results using a radar chart. Then, a usability study with 29 new participants was performed. The presentation of the UX evaluation results can be seen in Section V.

IV. UX Improvements

In the first usability study of OMA-ML, a total of 104 UX issues were recorded. Some of the UX issues were minor, such as misunderstandings of button functionalities due to ambiguous icons or labels. For example, the dataset upload button depicted a cloud icon. This led to confusion with some participants, as they believed the dataset would be uploaded into a cloud service. In fact, most issues were major usability problems related to the participants having issues understanding what to do on a page or with elements on a page.

We identified three problems with OMA-ML which required a rework for better usability: (A) First-time user onboarding: when participants used the platform for the first time, they were unsure how to proceed or what to do; (B) Self-descriptiveness: Participants from both user groups had difficulties understanding what some of the displayed information meant or what they were supposed to do; (C) Explainable AI: The information provided by the XAI modules were too convoluted that even AI Experts did not understand what they were looking at and quickly lost interest.

To address the first two problems, we followed the 10 usability heuristics [26], most importantly, heuristic number 10: *Help and Documentation* by implementing different types of help systems. Two types of help systems can be used to help a user: *Proactive Help*, and *Reactive Help* [27]. The goal of Proactive Help is to help the user familiarize with an a user interface. This can be achieved by one of two revelations: (1) *Push Revelations*: The application provides help context without regard to the user's task, (2) *Pull Revelations*: the applications provide contextual information to the user's task. The second help system type is *Reactive Help*, which aims to answer questions and troubleshoot problems [27].

An AI system may provide a better UX if both help system types are present. Within OMA-ML, this is accomplished by providing an *interactive walkthrough* and contextual help using *tooltips* for proactive help, as well as a *documentation and search* pages for reactive help.

[3]https://www.iso.org/obp/ui/#iso:std:iso:9241:-110:ed-2:v1:en

[4]https://www.iso.org/obp/ui/#iso:std:iso:9241:-110:ed-2:v1:en

The XAI problem was addressed by reworking the modules. The existing modules were replaced by packages developed by the data science community. While these packages do not advertise with a focus on usability, they are popular based on their GitHub stars rating. Having an understandable XAI module is imperative for any AI platform. It helps the user understand their data and ML models. Moreover, it may increase the trust in the AI platform [28]. Making the AI platform more transparent and providing an understandable explanation is important for adopting the AI platform [29].

In the following part, the individual components used to improve the UX of OMA-ML are presented.

Interactive Walkthrough

An interactive walkthrough is a technique used for more complex applications to facilitate onboarding for new users. Onboarding is the process during which users get familiar with a new interface [30]. While it is recommended to let users experience the application independently and that tutorials such as a walkthrough may have no positive impact [31][32], they could be helpful in the context of complex AI systems, specifically AI platforms such as OMA-ML. An interactive walkthrough may ease the onboarding, enabling them to learn by doing [30]. In Fig. 1, a screenshot from the OMA-ML home dashboard page with the enabled interactive walkthrough can be seen. The current walkthrough step explains the card *Recent datasets* and instructs the user to select a dataset to proceed.

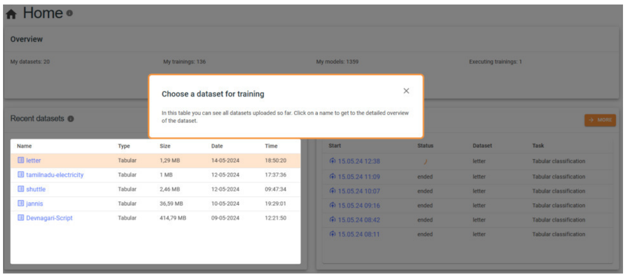

Fig. 1. OMA-ML home dashboard page with enabled interactive walkthrough

The interactive walkthrough greets first-time users upon their first login and should be like a practice run of the AI system. The OMA-ML walkthrough covers the user interaction concept [6]. At any point during the walkthrough, the user can prematurely exit and explore the platform independently. However, the platform offers the option on the documentation page to restart the walkthrough whenever the user wishes.

Documentation and Search

Documentation is an important part of UX. The main goal of documentation for reactive help is to help with user questions, troubleshoot their problems, and provide further detailed documentation for users aspiring to become expert users [27]. To achieve this, the documentation should follow some guidelines [27]: (A) It must be comprehensive and detailed; (B) it should be written following the rules of the web [33]; (C) it should make use of graphics and videos as secondary information source; (D) optimize for search; (E) group help topics into relevant categories; (F) highlight top content that is frequently viewed.

In Fig 2, a screenshot from the documentation page of OMA-ML can be viewed.

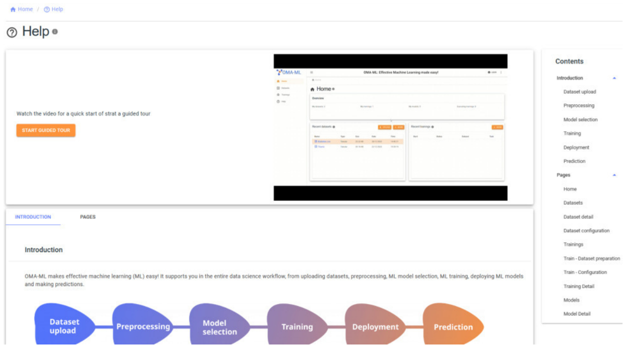

Fig. 2. OMA-ML documentation page

The documentation page consists of two sections. In the upper section, the user has a button to restart the interactive walkthrough and can view an explanatory video that follows the user interaction concept [6] and explains the process and individual pages.

The lower section provides graphical and brief written documentation for the individual steps of the user interaction concept [6] and each page within OMA-ML. Quick access links are available for the user on the right of the documentation page, listing the process steps and individual pages.

Furthermore, search functionality is available, as shown in Fig. 3. The search function aggregates all the knowledge from the underlying Ontology (See [34] for more information) and the documentation page.

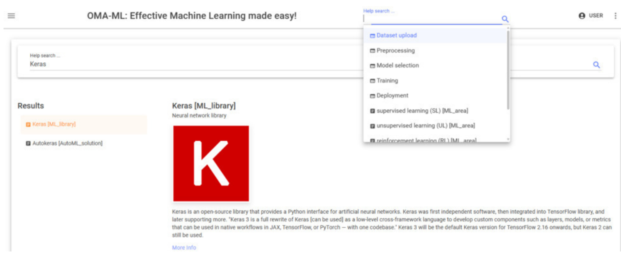

Fig. 3. OMA-ML search page

A user can search any keyword used within the platform and is then presented with a search result page. Depending on the search result, a written explanation with a graphic is shown or the corresponding help page section is displayed. In this example, the search word was *Keras* and the result are Keras the ML library[5] and the AutoML solution AutoKeras[6].

[5]https://keras.io/
[6]https://autokeras.com/

Tooltip

A tooltip is a brief, informative message that appears when a user interacts with an element in a graphical user interface (GUI) [35]. Tooltips are one method that can be used as a Pull Revelation for the user, providing information at the moment it is needed [32]. However, it is important to respect guidelines when incorporating them in an AI system [35][32]. Most importantly, they shall not be used to provide vital information for the user to complete their task and be used consistently. This was one of the major UX issues in the first OMA-ML study. Business domain experts and AI experts had difficulties understanding the meaning of the AI terminology in the context of the AI platform because there was no explanation. While business domain experts would not have the general background expertise to understand the meanings, AI experts would also question their expectations. For example, the word *training* in the context of data science refers to the process of training a ML model. In the context of OMA-ML, this references the Meta AutoML process of managing the training process of different AutoML solutions. This was addressed by including tooltips for any AI-specific term displayed in the platform. Depending on the nature of the element, one of two different approaches was used. First, buttons and selection options display a tooltip by hovering over them. For example, in Fig. 4, the tooltip briefly describes the selectable option of tabular classification.

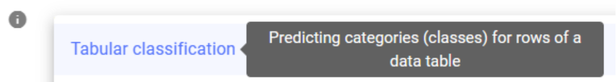

Fig. 4. OMA-ML tooltip help for tabular classsification

Secondly, a popup tips element was used for any element displaying information or requesting input. A popup tip is the sister element of the tooltip normally used for touchscreen devices [35]. It is paired with an "i" icon instead of being paired with an element. The OMA-ML example can be seen in Fig. 5. In this screenshot, the mouse hovers over the information icon next to a domain-specific term within the platform.

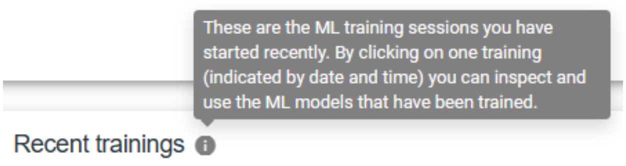

Fig. 5. OMA-ML tooltip help for recent trainings

In this case, the tooltip briefly explains what the card *Recent training* displays and what happens when clicking on one element within that card. This is a *progressive disclosure* approach [32], as it makes the existence of the tooltip visible to the user. Teaching the user information is not only available with interaction elements but also labels or elements to provide AI knowledge as well as task explanations.

XAI

Explainable AI provides a suite of techniques that enable human users to understand, trust and produce more explainable models [19]. It is an important aspect of an AI system, almost as important as the main AI functionality, as the trust a user has towards an AI system influences the adoption decision of the AI system [29]. AI Explainability can be accomplished by incorporating techniques from the four XAI categories [19]. (A) *Data Explainability*: provides visualisation of the data giving insight into the dataset; (B) *Model Explanation*: provides techniques to understand the decision-making within black and white box models; (C) *Feature-Based Techniques*: methods to describe how input features contribute to the model output; (D) *Example-Based Techniques*: Techniques to provide explainability using dataset specific examples.

XAI research provides a toolkit of techniques to make the data and models explainable [19]. However, there is also ready-to-use modules available covering one or multiple XAI categories.

Two third-party XAI ready-to-use modules were incorporated for the XAI module of OMA-ML. The first being *ydata-profiling*[7] for the Data Explainability. Ydata-profiling provides an Exploratory Data Analysis (EDA) by automatically performing univariate, multivariate, text, file analysis and discovers dataset challenges. In Fig. 6, a screenshot of the final EDA dashboard generated by data-profiling within OMA-ML can be seen.

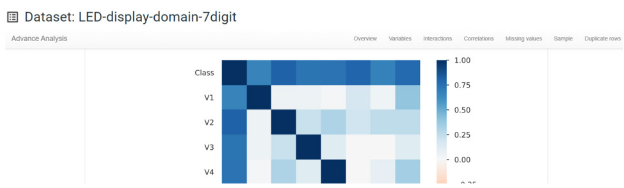

Fig. 6. OMA-ML dataset analysis

In the screenshot, only a section of the dashboard can be seen; this section displays the correlation matrix between dataset features.

The second XAI module is *explainer dashboard*[8]. This XAI module generates an interactive dashboard by analysing an ML model with a corresponding dataset. It supports techniques from the remaining XAI categories (Model Explanations, Feature-Based Techniques and Example-Based Techniques). In Fig. 7, a screenshot of the explainer dashboard can be seen within OMA-ML

Depending on the ML model, different information is displayed. In this case, the dashboard contains information about the importance of features, classification stats, individual predictions, what-ifs, and feature dependence. In the screenshot,

[7]https://github.com/ydataai/ydata-profiling
[8]https://github.com/oegedijk/explainerdashboard

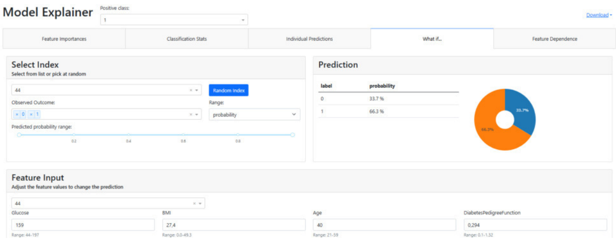

Fig. 7. OMA-ML explainable dashboard

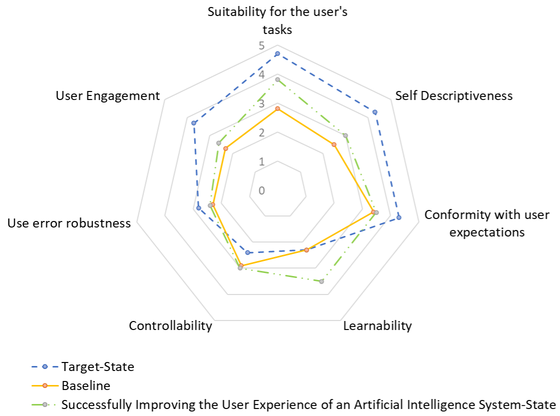

Fig. 8. Spider chart comparing the target state vs the results from the first and second Usability Study

the what-if tab is displayed. This tab provides functionality to experiment with the feature values and live evaluate how the model adjusts its prediction probability.

While neither module lists UX as a focus of their work, their popularity can be deducted from the number of GitHub stars they received (12.1k for ydata-profiling and 2.2k for explainer dashboard as of May 2024). The data science community is actively using and continuously improving these tools.

V. UX Evaluation of OMA-ML

Results from the Expert Review. In the first Expert Review [6], a total of four interaction principals with weak points were identified (suitability for the user's tasks, self-descriptiveness, conformity with user expectations and user engagement). Using the updated version of OMA-ML the second Expert Review could uncover that progress in the weak points could be made except for the interaction principle: conformity with user expectations. Furthermore, the learnability of OMA-ML was significantly improved. Although the learnability was already at its target goal, the new UX improvements, while aimed to improving other interaction principles, also increased the learnability. The resulting radar chart is shown in Fig. 8. The chart presents, for each of the 7 interaction principles, the different OMA-ML states on a scale of 1 to 5. The blue data points representing the target state, determined before the first Expert Review. The orange data points represent the baseline state after the first Expert Review. Finally, the green data points show the state of the updated OMA-ML version after the current Expert Review.

Results from the Usability Study. A total of 29 usability tests were performed, collecting a total of 120 usability problems. Each usability problem was assigned the interaction principle it infringes: suitability for the user's tasks (26), self-descriptiveness (27), conformity with user expectations (38), learnability (2), controllability (7), use error robustness (14), user engagement (6). Next, a severity rating was performed using the method described in Section III and potential resolution approaches added to each usability issue. Compared to the first Usability Study, the majority (78) of the usability issues have a severity rating of 2 (minor usability problem) or lower. Some of the more notable issues were:

1) XAI module: when the user wants to open the XAI explainer dashboard in some cases the dashboard did not load and causes errors visible to the user;
2) walkthrough: in some instances, the user was unaware of the required action to proceed with the walkthrough and became stuck.

VI. Conclusions and Future Work

UX focuses on creating a positive and meaningful experience for users and takes on a critical role during the design and development phase of any application. A bad UX can lead to rejection by the user. This is of particular importance when it comes to AI systems. As one part of UX, the usability gets determined by the trust of the underlying AI system. This is especially important to AI platforms such as OMA-ML. As without trust, the user may not adopt the platform. However, UX has not yet been a major focus in AI research. Nonetheless, the XAI research area is providing a suite of tools to support AI systems to provide explainability and trust in AI systems.

For the purpose of understanding and successfully improving the UX of an AI system, it is important to take an *iterative* qualitative and user-centric research approach. Using Expert Review and Usability tests based on the 7 interaction principles. The Expert Review uncovers UX issues, and the Usability Tests help to find usability problems from the target user group's perspective. Afterwards, the issues are resolved, and the updated version should be re-evaluated to uncover further UX issues and weak points. Using the case study of OMA-ML, we could show that the UX improvements to the interface and new XAI modules improved the platform's UX in 3 of the 4 interaction principle weak points previously uncovered after the initial UX evaluation.

While OMA-ML is not yet reaching its target state in all interaction principles, further UX improvements may be seen after the next UX evaluation iteration. The Usability study found a total of 120 new UX issues. After resolving these issues, a new iteration of the UX evaluation can be performed, potentially uncovering new ways to improve OMA-ML. Performing iterative UX evaluations per our recommendations can lead to successfully improving the UX of an AI system, potentially leading to more human-centered AI.

ACKNOWLEDGMENT

This work is funded by the German federal ministry of education and research (BMBF) in the program Zukunft der Wertschöpfung (funding code 02L19C157), and supported by Projektträger Karlsruhe (PTKA). The responsibility for the content of this publication lies with the authors.

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