

Interaction Paradigm Methodology (Initial)

Deliverable D4.4

WP4 - Human AML Interaction



This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 952091.

Consortium



ALGEBRAIC AI



Champalimaud
Foundation



EPROSIMA
The Middleware Experts



German
Research Center
for Artificial
Intelligence



TECHNISCHE UNIVERSITÄT
KAISERSLAUTERN

uc3m



Project

Title: ALMA: Human Centric Algebraic Machine Learning
 Acronym: ALMA
 Coordinator: Proyectos y Sistemas de Mantenimiento SL (eProsima)
 Grant agreement: 952091
 Call: H2020-EIC-FETPROACT-2019
 Program: Horizon 2020
 Start: 01 September 2020
 Duration: 48 months
 Website: <https://alma-ai.eu>
 E-mail: alma@eprosima.com
 Consortium: **Proyectos y Sistemas de Mantenimiento SL (eProsima) (EPROS)**, Spain
Champalimaud Foundation (CF), Portugal
ALGEBRAIC AI (ALG), Spain
German Research Center for Artificial Intelligence (DFKI), Germany
Inria (Inria), France
TU Kaiserslautern (TUK), Germany
FIWARE Foundation e.V. (FF), Germany
Technical Research Centre of Finland (VTT), Finland
Carlos III University (UC3M), Spain

Deliverable

Number: **D4.4**
 Title: **Interaction Paradigm Methodology (Initial)**
 Month: 18
 Work Package: WP4 - Human AML Interaction
 Work Package leader: Inria
 Deliverable leader: National Institute for Research in Digital Science and Technology (Inria)
 Deliverable type: R: Document, report
 Dissemination level: Public (PU)
 Date of submission: 2022-03-16
 Version: v1.0
 Status: Not finished

Version history

Version	Date	Responsible	Author/Reviewer	Comments
v1.0	2022-02-28	Inria	Janin Koch	Draft
v1.1	2022-03-10	Inria	Janin Koch	Partial Revision
v1.2	2022-03-14	Inria	Janin Koch, Wendy Mackay, Vitor Fortes Rey	Partial Revision
v1.3	2022-03-16	Inria	Janin Koch, Wendy Mackay, Vitor Fortes Rey	Revision

Executive summary

In this document, Deliverable D4.4 - Interaction Paradigm Methodology (Initial), we report the results from our exploratory research into new interaction methodologies for enabling more user-centered human-AML interaction.

The objective of this deliverable is to extend current participatory design methodologies to incorporate the role of an intelligent system into the interaction loop, so we can develop human-AML interaction using a human-centred approach. The ultimate goal is to identify new visualization methods that will help novice users understand the state of the algorithm in terms they can understand, control and adapt.

We describe our first participatory design workshop for the use case of expressive gesture typing, where we investigated potential new interaction methodologies for creating a more explainable and controllable human-AML interaction. In Deliverable D4.1 - Human-AML Interaction (Initial), we outline the potential of AML for human-centred explainability, which forms the basis for this deliverable. We introduce the potential of participatory design for exploring human-AI interaction and the state-of-the-art in current gesture typing research. We explain in detail how to conduct this form of participatory design study, and how it can help develop new visualizations.

We also report the initial results of the first workshop, which resulted in new visualizations that support human-AML interaction. These are incorporated into the prototype of human-AML for expressive gesture typing, reported in Deliverable D4.7 - Working Prototype and designs (Initial).

This deliverable will be followed by D4.5. Interaction Paradigm Methodology (Revised), which will continue our exploration of new visualization for human-centred AML interaction methodologies. We will propose a new interaction paradigm in Deliverable D4.6 - Interaction Paradigm Methodology - Final.

Contents

Executive Summary	3
Contents	4
1 Introduction	6
2 Background	7
2.1 Gesture Typing	7
2.1.1 Explainability of Gesture Typing	7
2.2 Participatory Design (PD)	8
2.2.1 Participatory Design for Human-AI Explainability	8
3 Participatory Design Workshop for Gesture Explainability	9
3.1 Participants	9
3.2 Setup	9
3.3 Procedure	9
3.4 Data Collection	11
4 Workshop Results	11
4.1 Visualizations for one Feature	11
4.2 Visualizations for all Features	13
5 Discussion	13
5.1 Explicit vs. Implicit visualization	13
5.2 Dynamic vs. Instructive visualization	14
6 Conclusions	15
References	16

1 Introduction

In this deliverable, Deliverable D4.4 - Interaction Paradigm Methodology (Initial), we report findings from our exploratory research into new interaction methodologies for enabling more user-centered human-AML interaction.

The long-term objective of Interaction Paradigm Methodology WP (D4.4-6) is to explore how interaction with an AML based Machine Learning and Reasoning system affects the user experience and determines the corresponding requirements for AML based interactive machine learning. General measures of personality and emotional state are insufficient to capture the user's unarticulated, in-the-moment changes in context and goals, and thus cannot be accounted for directly by an algorithm. Instead, we intend to develop new interaction design methods that identify and take advantage of the disparity in the skills of both humans and AI algorithms. We will further develop new ways to visualize the AML's interpretation of the user's behavior in a form users can understand. We will also develop new ways for users to express their current state and changes in goals, to dynamically change the course of the interaction.

This current deliverable is a first step toward this goal. The use case for developing new interaction visualizations and methodology is expressive gesture typing, based on our earlier work on Expressive Keyboards [1]. Expressive Keyboard is a smart phone application that takes advantage of rich variation in gesture-typed input to produce expressive output. Different features, i.e. speed, curviness, inflation and acceleration of the typing gestures are mapped to different colors. This allows users to vary their visual expression using rich underlying information during gesture typing. In earlier studies, we identified a challenge for participant to estimate and control the way the system will interpret their gesture, resulting in 25% deleted word, even if those were spelled correctly. Based on the potential of AML for explainability, we aim to develop a more understandable and controllable way to interact with expressive gesture keyboards.

We identify three potential advantages of AML models when compared to other machine learning models, such as some deep neural networks, which are recognized as less conducive to interpretability in the context of explainable AI (XAI) [2]:

- AML-models have a fundamentally simple structure. They comprise only three layers: inputs – atoms – outputs. An atom can be linked to one or more inputs and is said to be present in an example if at least one of those inputs is present. AML-models expand as they learn patterns from training data, though the simple three-layer structure persists.
- The core AML algorithms check that the human-defined constraints are maintained in the subsequent binary relationships between inputs and outputs that are learned as new atoms are generated during training. The overall integrity of the AML-DL model is maintained however large the number of atoms grows to be.
- AML-DL rules can be traced back to human-defined policies, for example, those that provide the basis for human-defined work procedures. As new atoms that are generated during training conform to the AML-DL model's human pre-defined rules, AML-models become interpretable. That is, humans can interpret how the model uses inputs to generate outputs [3].

While all three fundamental aspects of AML are crucial for explainability, the last highlights this potential.

We are interested in exploring how to leverage the power of participatory design to create better human-AI interactions [4, 5, 6]. Since one of the core principles of participatory design is to include users as co-designers, the outcomes typically lead to a better understanding and interaction with current technology. We continue in this tradition by reporting the findings of a Participatory Design workshop for building new visualizations that help the controllability and explainability of machine learning techniques such as AML.

This deliverable (D4.4) focuses on designing human-AI interactions and how to increase explainability and controllability when interacting with an AI model. It also offers additional insights into the fundamental notion of human-centered explainability.

This deliverable first describes gesture typing and the participatory design methodology (PD). It then describes the setup and procedure for the PD workshop, and concludes with the results and how they have influenced our approach to exploring new interaction methodologies for human-AI interaction for expressive gesture typing.

2 Background

We first provide a short overview of state-of-the-art of gesture typing research and highlight the particular challenges associated with the explainability and controllability of these approaches. We then introduce the background and strengths of participatory design approaches and its application in recent work in the design of human-centred human-AI interaction.

2.1 Gesture Typing

Gesture keyboards let users enter text by drawing a line that connects all the letters in a word (i.e., a word-gesture) [7]. Word-gestures are not unique for each word, but can be robustly matched using a combination of kinematic models, multidimensional distance metrics, and language models to resolve ambiguities [8]. Gestures that vary significantly may thus still register as correct. A study conducted by Reyat et al. [9] found that although two-thumb touch typing in a lab setting (i.e., sitting in a calm room) led to a higher text entry rate with fewer errors, one-handed gesture typing is particularly more effective under conditions of *situational impairment* [10] such as walking.

Arguably, gestures may also contain as rich information as in handwriting, and thus open a potential opportunity in conveying situational information or intent to enhance communication in digital writing. However, the gesture typing technique commonly treats gesture variations as “noise” and the recognition engine only aims to identify the correct word. By contrast, Expressive Keyboards “recycle” the gesture-typing variations and transform them into rich output such as parametric text [1] or emojis [11]. Similarly, TapScript [12] generated dynamic handwriting-like font based on touch-typing variations and the smartphone’s rotations. Researchers have also leveraged typing variations on physical keyboards to format text [13] or generate dynamic visualizations [14]. Users reported being able to recognize situational variations (e.g., due to walking) just by looking at the dynamic output generated with TapScript [12].

2.1.1 Explainability of Gesture Typing

A common issue in mapping input variations (i.e., features) to output characteristics is the tension between accuracy, deliberate control (i.e., explicit), and situational variations (i.e., implicit) [12, 1]. Expressive Keyboards investigated deliberate user control over three gesture features (curviness, gesture typing speed, and inflation) [1], and found that users were more successful in producing the desired output characteristics when they focused on how the output looks like (e.g., make the text green) compared to if they were given explicit instructions related to the gesture features (e.g., draw a curvy gesture). That said, they sometimes erased a correct word to modify the output characteristics (up to 24% of words in the evaluation) [1]. Using dynamic human-AI interaction for gesture typing could open up the opportunities to support deliberate control through explainable features, thus, allowing users to focus on the output characteristics while minimizing trial-and-error efforts.

2.2 Participatory Design (PD)

One of the earliest substantial contributions of Scandinavian research to HCI was Participatory Design (PD) [15]. PD was created at a time when computers were beginning to revolutionize the way people worked. It was designed as a tool to assist employees and their unions in influencing the changes that occurred when computers were implemented widespread in the work place. Scandinavian PD focused on strengthening the interaction with technology, especially when conflicts or errors arose. They explored specific solutions to the challenges of the moment, as well as designed future possibilities and alternatives. Today, PD plays a role in many countries and embraces a wide range of perspectives [16].

Most current PD is focused on facilitating direct engagement between users and designers in co-design processes to react to everyday concerns of usage, whether through technology or otherwise (see also [17, 18]). HCI as a whole has adopted this method, especially for addressing current issues with products and technology solutions. Since users are involved as co-designers in participatory design, the results lead to a better understanding and interaction with existing technologies rather than radical changes in technology or behavior [16]. While there are numerous applications of PD in HCI literature (see, for example, [19]), a review of PD literature published in the Proceedings of the Participatory Design Conference (PDC) from 2002 to 2012 [20] identified five fundamental aspects of PD: politics, context, product, people, and method (Table 1).

Politics	People who are affected by a decision should have an opportunity to influence it
People	People play critical roles in design by being experts in their own lives
Context	The use situation is the fundamental starting point for the design process
Methods	Methods are means for users to gain influence in design processes
Product	The goal of participation is to design alternatives, improving quality of life

Table 1: Fundamental aspects of Participatory Design [20]

While the authors conclude that most approaches of designing with users (e.g. Human Computer Interaction, User Centred Design, and Interaction Design) address some of the five fundamental aspects of PD, with the possible exception of Politics, they argue that addressing a combination of all these aspects constitutes a promising scope for the impact of participatory design in practice [20]. This holistic view on the users understanding, context and product allows designers to create better solution for challenging problems like human-AI interaction.

2.2.1 Participatory Design for Human-AI Explainability

In recent years researchers in human-AI interaction have started leveraging the power of PD for designing better human-AI interactions (see e.g. [4, 5, 6]). Mucha et al. highlights the use for "participatory design spaces as an approach to inform the human-centered design of Human-AI Interaction focusing on XAI in expert domains" [5, p. 4]. They argue that, like human-human communication, each human-AI explanation has two actors: the explainer and the explaine. As Clarke et al. [21] have already stated regarding human interactions, in order for these two actors to interact with each other, a common ground must be established. As a result, explanations must be designed to be understood by the individuals or groups to whom they are directed. In other words, the explainer must speak the explaine's language, and hence AI explanations must be developed in a human-centered way [5]. The emphasis on human understanding, which is strongly rooted in the practice of PD, thus provides an opportunity to explore such paths.

3 Participatory Design Workshop for Gesture Explainability

We held a two-hour participatory design workshop with a diverse group of participants to investigate the potential of explainable human-AI interaction for gesture typing. In the following sections, we will briefly go through the participants, the setup, and the workshop structure.

3.1 Participants

The participatory design workshop included two groups of three participants, with two external participants and one author. Each group included one software engineer, one HCI professional and one practising designer.

3.2 Setup

The workshop was held in a Fablab, (Fabrication Laboratory) which provided sufficient space for the two groups to work without interfering with each other. We provided craft materials including colored paper and pens, as well as smart phone interface templates (see Fig. 1).

3.3 Procedure

The workshop lasted for two hours and was divided into four phases: *Introduction*, *Exploration*, *Sketching*, and *Reflection*.

Introduction: We began with a brief presentation that described the expressive keyboard application [1]. Expressive Keyboards is a smart phone application that takes advantage of rich variation in gesture-typed input to produce expressive output. Different features, i.e. speed, curviness, inflation and acceleration of the typing gestures are mapped to different colors. This allows users to vary their visual expression using rich underlying information during gesture typing (see Fig. 2).

We presented selected insights from an earlier experiment that evaluated the Expressive Keyboard, focusing on those relevant for explainability and control. We discussed the difficulty that users had when they tried to estimate and control how the system interpreted their gestures, since 25% of the time they deleted words and tried again to obtain the desired expressive output, even if the word was spelled correctly but the visual expression was not as desired.

As a logical next step, we framed the questions that would guide our workshop as follows. What if:

1. the system could communicate why a gesture input results in a specific expression;
2. the user could actively influence the system interpretation for a desired output; and
3. both, system and user, could re-adapt through interaction to achieve a more controllable and desirable outcome.

We then provided to every participant a phone that had the Expressive Keyboard application installed and asked them to try typing and reflect on the system and internalize the idea of expressive gesture typing.

Exploration: The second phase lasted for 15 minutes. Each group received a method card that defined three roles:

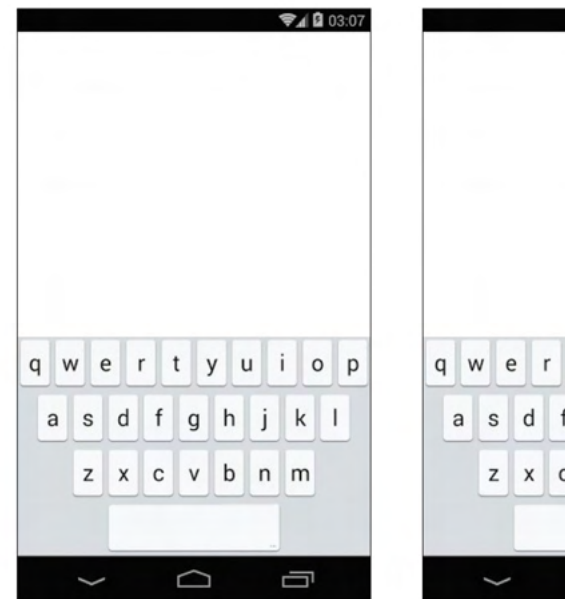


Figure 1: Application template

P2-F-00 a Try to make each phrase a different shade of green breathing is difficult	P0-N-IV b Go outside of the keyboard time to go shopping	P8-N-HP2 c Draw for 1) your niece 2) your best friend, 3) your parent earth quakes are predictable	P4-N-HE1 d Express how you feel 1) happy, 2) frustrated, 3) sad we went grocery shopping
breathing is difficult	time to go shopping	earth quakes are predictable	we went grocery shopping
breathing is difficult	time to go shopping	earth quakes are predictable	we went grocery shopping
breathing is difficult	time to go shopping	earth quakes are predictable	we went grocery shopping

Figure 2: Examples from the original paper. Successful color control through gesture: a) bright-green indicates curviness, dark green indicates straight lines; b) inflating the gesture increased red values; c) Participant changed the color deliberately for different recipients; d) Participant made curvier gestures with more detours for ‘happy’, and slow and less curvy gestures for ‘sad’.

- **Instructor:** Read the instructions silently and instruct the user how to achieve the goal without using certain taboo words
- **User:** Gesture type and try to achieve the goal indicated by the instructor
- **Observer:** Observe and take notes of the instructor’s strategies and the user’s actions

Each group received a different card and each card contained *the goal*, *instructions* how to achieve this goal and *taboo words* the instructor was not allowed to use (see Fig. 3). This method allowed the participants to brainstorm different actions and to collect ideas as to how the gesture instructions might be provided and understood by the user. The taboo words helped each instructor to think “outside of the box”, and explore other alternatives such as associations or sounds.

We then encouraged each group to extend and reflect upon the interaction between the instructor and the user during the exploration phase, and the strategies they used to succeed.

Group Black

Goal:

The user should write 3 times in black:
Black panthers are hiding in the shadows!

Instruction:

Constant Speed

Constant Speed: keep a constant speed;
Keep straight lines



Taboo Word:

- Constant
- Straight

Speed-up (or Slow-down)



Group Red

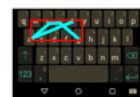
Goal:

The user should write 3 times in bright red:
Red pandas would love being red!

Instruction:

Normal

Inflation: The user has to overshoot;
make a bigger gesture



Taboo Words:

- Overshoot
- Inflate(d)

Inflated



Figure 3: Examples of method cards provided to the different groups.

Sketching: In the third phase lasted, we asked each group to sketch dynamic visualizations of the initial instruction they received for 15 minutes. We encouraged them to translate their strategies into visualizations based on their initial notes, and also told them they could expand upon their ideas during the process. The participants were invited to include embodied or visual associations as well as sketch as many ideas as they could.

At the end of this phase, we explained the four features that affect the color of the font and explained how to combine them. We then asked each group to transform and expand their initial strategies into visualizations so that they considered all four dimensions.

Reflection: In the fourth phase, each group presented their work and reflected on the previous two

sketching exercises. Participants were encouraged to discuss their ideas, ask each other questions, and build upon each other's ideas.

3.4 Data Collection

We collected the written notes and sketches of all participants, as well as our own hand-written notes based on our observations during the exercises. We also video recorded and took photographs during the workshop.

4 Workshop Results

This section describes selected results from the PD workshop, and highlights the preferences expressed by the participants during the final reflection phase. We also include additional observations that can inform human-AI interaction. The first group (A) were assigned “speed variation” as their initial feature, i.e. the larger the variance in gesture speed, the bluer the text. The second group (B) were assigned “inflation” as their initial feature, i.e. the larger and more exaggerated the gesture, the redder the text.

4.1 Visualizations for one Feature

In the initial exploration phase, the **Group A** instructor focused on rhythm “Now, try to be very even here”, rather than using the taboo words of slowing down or speeding up. Many of the suggestions were thus related to rhythm and the contrast of breaks vs. writing.

Rhythm: Rhythm is one method for instructing or guiding users to change the accelerating of their gesture. Group A investigated various approaches to supporting the feeling of rhythm or off-rhythm. To provide a sense of rhythm, suggestions ranged from actual metronomes to vibration signals during gesture typing (see Fig. 4.1 and 4.2).

Given that the system already knows the word beforehand, Group A suggested a karaoke like ‘follow the ball from letter to letter’ approach. This approach is often used in karaoke settings to indicate longer and shorter parts of a word (see Fig. 4.3).

Visualize acceleration: The visualization of acceleration in real time was the focus of a second set of ideas. In the final show case, Group A emphasized the idea that by visualizing time horizontally and acceleration vertically, the profile of a word gesture looks similar to a heartbeat. This association between gesture expression and word heartbeat was appreciated by other participants in the other group as well (see Fig. 4.4).

Another suggestion made by the group was to visualize acceleration using sound. In particular, by employing a Shepard–Risset glissando, which is a sound made up of a superposition of sine waves separated by octaves and allows for the creation of tones that appear to rise and fall in pitch continuously. This would provide dynamic feedback on acceleration without interfering with the visual task of gesture typing (see Fig. 5.1).

Breaks vs. writing: A final set of concepts looked at the ‘in-between’ space, between breaks and fast writing. Some ideas in this category show potential for breaks or acceleration while gesture typing, assuming the word is known. Others delve into Morse code concepts to visualize the difference in length and gaps between writing (see Fig. 5.2).

Group B gave instructions based on (exaggerated) movements and large gestures during the initial exploration phase such as “Can you make it bigger?” and “The more excited you are, the better it will work!” (I-Instructor). As a result, a number of suggestions were made regarding associations with boldness, as well as what it means to have an exaggerated path.



Figure 4: Examples of visualizations (left to right): 1) Metronomes, 2) Vibration pattern, 3) Heartbeat, and 4) 'Follow the ball' visualization

Boldness: One strategy proposed in the final presentation was to use a 'flying fairy' metaphor to indicate a potential path that is bolder than the keyboard, encouraging the user to achieve the desired exaggerated gesture on the virtual keyboard (see Fig. 5.3).

Exaggerated paths: Another concept was highlighting different paths based on path prediction, essentially showing an option in direction and strike length indicating the system's potential interpretation (see Fig. 5.4).

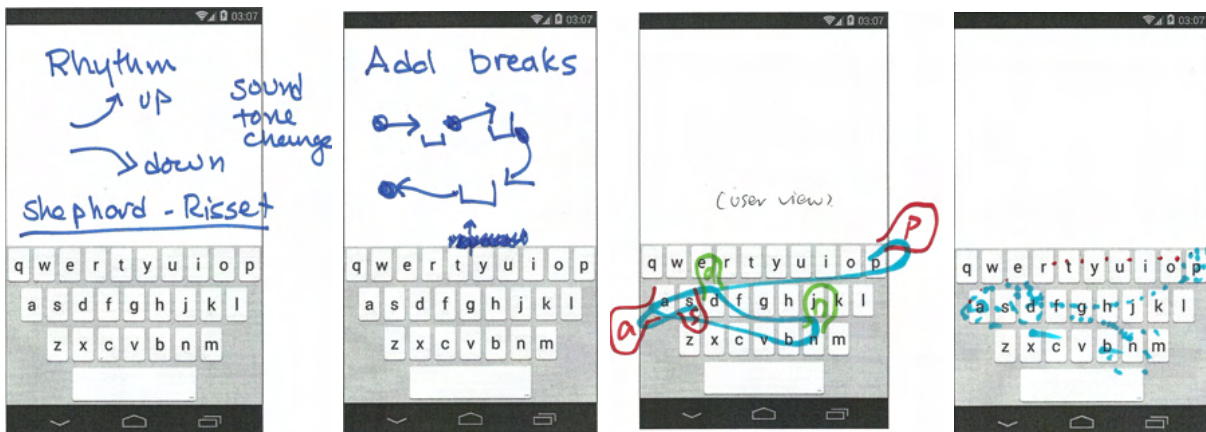


Figure 5: Examples of visualizations (left to right): 1) Shephard-Risset sound rhythm, 2) Breaks and write, 3) 'Flying fairy' suggestion, and 4) Path prediction visualization

Overall, Group B believes that dynamic feedback while typing would be too fast to incorporate into an action. As a result, prior to using the Expressive Keyboard, a sort of training version was generally preferred.

4.2 Visualizations for all Features

In the second sketching phase, we explained the four features that affect the color of the font. The following ideas include both generalizations from the first phase, as well as new ideas.

Visualization space: One popular concept was the multi-dimensional visualization of the color space in relation to the interaction space. The four dimensions introduced as relevant for the gesture output would thus be the dimensions, while the space between them would show the color at this level of combination. A person gesture typing would be able to see where he or she is in the space while typing (see Fig. 6.1).

Guiding paths: One suggestion made in the final presentation was to color-light the edges of a key to show what color it will be if the user navigates in that direction. This can assist users in deciding how to proceed while typing. The direction, on the other hand, is directly related to the next letter, so the system must either know or predict the expected word (see Fig. 6.2).

Some concepts are also aimed at teaching users how to use different gestures by providing alternative paths. For example, when a user deletes a word, the system may display the possible path to achieving a specific color on the virtual keyboard for that word (see Fig. 6.3).

Gamut range visualization: The final concept explicitly visualizes the gamut range of the different dimensions and the placement of the current gesture. While this does not provide direct feedback on the output, it can assist users in better understanding how to control the system (see Fig. 6.4).

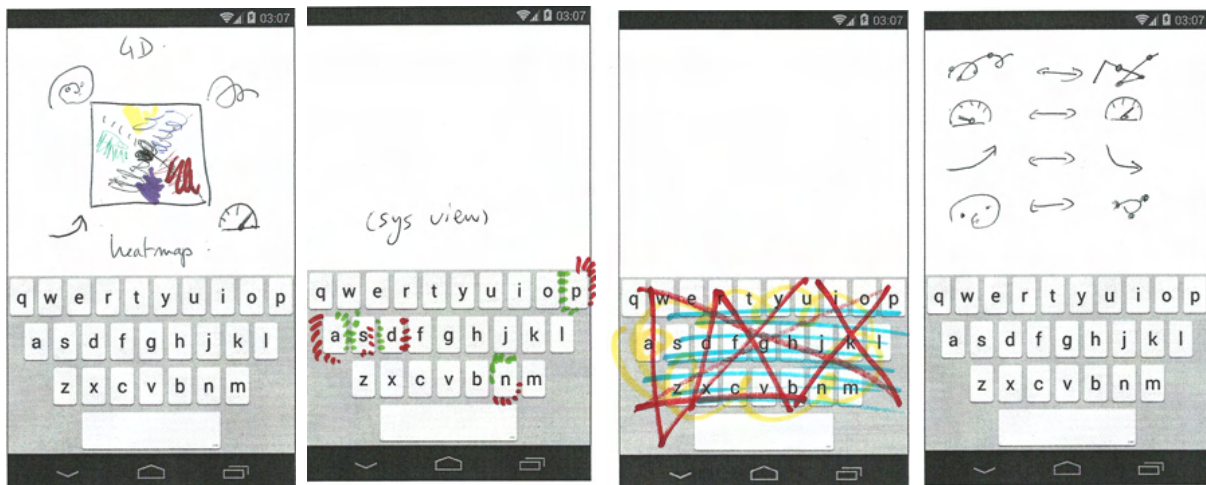


Figure 6: Examples of multi-dimension visualizations (left to right): 1) Visualization space, 2) 'Edges of a key', 3) Alternative paths, and 4) Gamut range visualization

5 Discussion

A number of valuable concepts were introduced during the PD workshop. Here, we focus on two dimensions that participants explicitly highlighted: *Explicit vs. Implicit visualization*, and *Dynamic vs. Instructive visualization*.

5.1 Explicit vs. Implicit visualization

The conflict between deliberate control (i.e., explicit), and situational variations (i.e., implicit) is a typical challenge in mapping input variations (i.e., features) to output characteristics [12, 1]. As a result, it is not

surprising that the results show a range of concepts ranging from explicit to implicit visualization.

Explicit visualizations express the feature dimension directly, as in the 'Gamut range visualization' (see Fig. 6.4). Other visualizations, such as providing a clear path (see Fig. 5.4) or alternative path predictions (see Fig. 6.3), also directly address the underlying features. The focus on input parameters and how to better control them is common to all of these approaches. In the context of previous research results in the Expressive Keyboard study [1], input focus was considered most effective in adjusting gestures to express the desired outcome, but it was also reported as one of the most difficult factors to manipulate. As a result, our prototype (which is discussed in detail in Deliverable D4.7) includes one explicit visualization approach for providing the user with explainability and controllability when interacting with the AML model.

Implicit visualizations are strongly associated with the user's perspective and experience, with two major distinctions within this concept. The first concerns the personal experience of gesture typing, such as rhythm (see Fig. 4.1-3), whereas other visualizations in this category focus on the outcome of the gesture, such as Visualization space (Fig. 6.1). While both address the user's experience implicitly, the implications of personal experience or relation to the desired outcome are fundamentally different. While focusing on output has been shown to help users perform better in expressive typing [1], there is growing interest in the research community for human-AI collaboration to include and leverage personal experiences through personalization when interacting with intelligent systems [22]. However, integrating personal experiences such as sounds, vibration, or rhythm into a system's interaction approach commonly requires some form of calibration to match the experience of an individual user. Since the goal of the prototype for expressive gesture typing is to encourage the general public to use and express themselves and their situational environment in a more creative way, we will only explore output-oriented visualization, as shown in Fig. 6.1. Personalized human-AML interactions, on the other hand, may well be a promising next step.

5.2 Dynamic vs. Instructive visualization

Controlling interactions while interacting can be challenging, especially when speed variation is a parameter of the considered input.

Instructive visualization refers to approaches that provide guidance to achieve a desired goal. For example, Group B explained that dynamic feedback while typing may be too fast to incorporate into the current action and that control should instead be provided by prior system training. Visualizations that take this more instructive approach commonly require prior knowledge of the word and/or the desired expression, as shown in Fig. 6.2-3 or Fig. 6.1. This approach is in line with behavior observed during the workshop and which was also reported in [1], where users removed and rewrote text until they achieved a particular desired outcome. Providing guidance to optimize for a specific gesture, on the other hand, has been shown in previous research to prevent users from exploring and creating new, more personal expressions [1]. This limits the interaction between human and AI systems in exploring a creative space together, as the user learns to instruct the tool rather than work with it.

Dynamic visualizations, on the other hand, refer to the ability to explain input or output features in real time. Using dynamic human-AI interaction for gesture typing could open up the possibility of supporting deliberate control through explainable features, allowing users to concentrate on the output characteristics while reducing trial-and-error efforts. Examples for dynamic interaction concepts are the "Gamut range visualization" for explaining input features recognition (see Fig. 6.4) and Visualization space for describing output feature interpretation (see Fig. 6.1). These visualizations require 1) continuous monitoring of typing behavior and 2) updating the visualization to describe either the input or output effect of the current interaction. While this may create information overload (see Group B's comment), it also offers a unique opportunity for explaining the system's understanding while allowing the user to control and shape the system's interpretation. Therefore, Deliverable D4.7 focuses on dynamic visualization for human-

AML interaction; however, we acknowledge that there is a potential research space between learnability, explainability, and control that we could address in a future deliverable.

6 Conclusions

This deliverable, D4.4 - Interaction Paradigm Methodology (Initial), reports the results of exploratory research into new interaction methodologies for enabling better user-centered human-AML interaction. We organized a participatory design workshop to investigate new potential interaction methodologies for creating a more explainable and controllable human-AML interaction for the expressive gesture typing use case. We discuss our insights and reasoning for effective visualizations that will be used in the final prototype to support human-AML interaction.

Our preliminary results suggests that there is an exciting research space between explicit and implicit interaction approaches for providing more explainable, controllable, and potentially personalized human-AI interaction. We also report on learnability and real-time controllability perspectives. While traditional machine learning approaches commonly target system learnability, either through instructions or training, we think that dynamic visualization has greater potential for human-AI interaction. While some of our participants expressed concern that dynamic visualizations might overload a user, all groups agreed on the importance of real-time guidance for controllability using explainability when working with intelligent machines.

The goal of this deliverable is to explore how to design human-AI interactions that increase explainability and controllability when interacting with an AI model. It also offers new insights into the fundamental notion of human-centered explainability. This deliverable will be followed by D4.5. Interaction Paradigm Methodology (Revised), in which we will continue our investigation of novel visualization approaches for human-centered AML interaction in order to offer a new Interaction Paradigm for the D4.6. Interaction Paradigm Methodology - Final deliverable.

References

- [1] Jessalyn Alvina, Joseph Malloch, and Wendy E. Mackay. “Expressive Keyboards: Enriching Gesture-Typing on Mobile Devices”. In: *Proceedings of the 29th Annual Symposium on User Interface Software and Technology*. UIST ’16. Tokyo, Japan: ACM, 2016, pp. 583–593. ISBN: 978-1-4503-4189-9. DOI: 10.1145/2984511.2984560. URL: <http://doi.acm.org/10.1145/2984511.2984560>.
- [2] Cynthia Rudin. “Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead”. In: *Nature Machine Intelligence* 1.5 (2019), pp. 206–215.
- [3] Scott M Lundberg and Su-In Lee. “A unified approach to interpreting model predictions”. In: *Advances in neural information processing systems* 30 (2017).
- [4] Douglas Zytke et al. “Participatory Design of AI Systems: Opportunities and Challenges Across Diverse Users, Relationships, and Application Domains”. In: (2022).
- [5] Henrik Mucha et al. “Towards participatory design spaces for explainable ai interfaces in expert domains”. In: *43rd German Conference on Artificial Intelligence, Bamberg, Germany*. 2020.
- [6] Evgeni Aizenberg and Jeroen Van Den Hoven. “Designing for human rights in AI”. In: *Big Data & Society* 7.2 (2020), p. 2053951720949566.
- [7] Shumin Zhai and Per Ola Kristensson. “The Word-gesture Keyboard: Reimagining Keyboard Interaction”. In: *Commun. ACM* 55.9 (Sept. 2012), pp. 91–101. ISSN: 0001-0782. DOI: 10.1145/2330667.2330689. URL: <http://doi.acm.org/10.1145/2330667.2330689>.
- [8] Per-Ola Kristensson and Shumin Zhai. “SHARK2: A Large Vocabulary Shorthand Writing System for Pen-based Computers”. In: *Proceedings of the 17th Annual ACM Symposium on User Interface Software and Technology*. UIST ’04. Santa Fe, NM, USA: ACM, 2004, pp. 43–52. ISBN: 1-58113-957-8. DOI: 10.1145/1029632.1029640. URL: <http://doi.acm.org/10.1145/1029632.1029640>.
- [9] Shyam Rey, Shumin Zhai, and Per Ola Kristensson. “Performance and User Experience of Touchscreen and Gesture Keyboards in a Lab Setting and in the Wild”. In: *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. CHI ’15. Seoul, Republic of Korea: Association for Computing Machinery, 2015, pp. 679–688. ISBN: 9781450331456. DOI: 10.1145/2702123.2702597. URL: <https://doi.org/10.1145/2702123.2702597>.
- [10] Jacob O Wobbrock. “Situationally-induced impairments and disabilities”. In: *Web Accessibility*. Springer, 2019, pp. 59–92.
- [11] Jessalyn Alvina et al. “Mojiboard: Generating Parametric Emojis with Gesture Keyboards”. In: *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*. CHI EA ’19. Glasgow, Scotland UK: Association for Computing Machinery, 2019, pp. 1–6. ISBN: 9781450359719. DOI: 10.1145/3290607.3312771. URL: <https://doi.org/10.1145/3290607.3312771>.
- [12] Daniel Buschek, Alexander De Luca, and Florian Alt. “There is More to Typing Than Speed: Expressive Mobile Touch Keyboards via Dynamic Font Personalisation”. In: *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services*. MobileHCI ’15. Copenhagen, Denmark: ACM, 2015, pp. 125–130. ISBN: 978-1-4503-3652-9. DOI: 10.1145/2785830.2785844. URL: <http://doi.acm.org/10.1145/2785830.2785844>.
- [13] Ken Iwasaki, Takashi Miyaki, and Jun Rekimoto. “Expressive Typing: A New Way to Sense Typing Pressure and Its Applications”. In: *CHI ’09 Extended Abstracts on Human Factors in Computing Systems*. CHI EA ’09. Boston, MA, USA: Association for Computing Machinery, 2009, pp. 4369–4374. ISBN: 9781605582474. DOI: 10.1145/1520340.1520668. URL: <https://doi.org/10.1145/1520340.1520668>.
- [14] Petra Neumann et al. “KeyStrokes: Personalizing Typed Text with Visualization”. In: *Eurographics/IEEE-VGTC Symposium on Visualization*. Ed. by K. Museth, T. Moeller, and A. Ynnerman. The Eurographics Association, 2007. ISBN: 978-3-905673-45-6. DOI: 10.2312/VisSym/EuroVis07/043-050.
- [15] Susanne Bødker. “When Second Wave HCI Meets Third Wave Challenges”. In: *Proceedings of the 4th Nordic Conference on Human-Computer Interaction: Changing Roles*. NordiCHI ’06. Oslo,

- Norway: Association for Computing Machinery, 2006, pp. 1–8. ISBN: 1595933255. DOI: 10.1145/1182475.1182476. URL: <https://doi.org/10.1145/1182475.1182476>.
- [16] Susanne Bødker and Morten Kyng. “Participatory design that matters—Facing the big issues”. In: *ACM Transactions on Computer-Human Interaction (TOCHI)* 25.1 (2018), pp. 1–31.
 - [17] Ditte Amund Basballe, Kim Halskov, and Nicolai Brodersen Hansen. “The Early Shaping of Participatory Design at PDC”. In: *Proceedings of the 14th Participatory Design Conference: Short Papers, Interactive Exhibitions, Workshops - Volume 2*. PDC ’16. Aarhus, Denmark: Association for Computing Machinery, 2016, pp. 21–24. ISBN: 9781450341363. DOI: 10.1145/2948076.2948078. URL: <https://doi.org/10.1145/2948076.2948078>.
 - [18] Kristin Lofthus Hope and Eva Amdahl. “Configuring designers? Using one agile project management methodology to achieve user participation”. In: *New Technology, Work and Employment* 26.1 (2011), pp. 54–67. DOI: <https://doi.org/10.1111/j.1468-005X.2010.00257.x>. eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1468-005X.2010.00257.x>. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1468-005X.2010.00257.x>.
 - [19] Liam Bannon, Jeffrey Bardzell, and Susanne Bødker. “Reimagining participatory design”. In: *Interactions* 26.1 (2018), pp. 26–32.
 - [20] Kim Halskov and Nicolai Brodersen Hansen. “The diversity of participatory design research practice at PDC 2002–2012”. In: *International Journal of Human-Computer Studies* 74 (2015), pp. 81–92. ISSN: 1071-5819. DOI: <https://doi.org/10.1016/j.ijhcs.2014.09.003>. URL: <https://www.sciencedirect.com/science/article/pii/S1071581914001220>.
 - [21] Herbert H Clark and Susan E Brennan. *Grounding in communication*. American Psychological Association, 1991.
 - [22] S Shyam Sundar. “Rise of machine agency: A framework for studying the psychology of human–AI interaction (HAII)”. In: *Journal of Computer-Mediated Communication* 25.1 (2020), pp. 74–88.