



Human-centric algebraic machine learning

Evaluation - Final

Deliverable D4.11

WP4 - Human AML Interaction



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Executive summary

AML Algebraic Machine Learning (AML) is a novel machine learning technique based on algebraic representations of data. Unlike statistical learning, AML algorithms are robust regarding the statistical properties of the data and are parameter-free. AML systems can retain what they learn, including sociocultural ethical practices for human–artificial intelligence systems. The aim of the EU-funded ALMA project is to study the mathematical properties of AML and to leverage them to develop a new generation of interactive human-centric machine learning systems. These systems are intended to minimize bias in order to facilitate trust while better enabling distributed collaborative learning.

This report corresponds to *Deliverable D4.11 - Evaluation - Final* of the ALMA project. The goal of this deliverable is to run a controlled laboratory experiment to determine the effectiveness of the different interaction techniques. This work builds on the design work presented in D4.4 - Interaction Paradigm Methodology (Initial) and the prototype described in D4.7 - Working Prototype and Designs (Initial). We evaluated the resulting AML-based gesture approach of *InSituBoard* with our previously published work on Expressive Keyboards. We present the benefits and limitations of using a AML-based approach based on our study results and conclude with a summary of our insights.

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Acronyms

AML Algebraic Machine Learning.

1 Introduction

This Deliverable D4.11 - Evaluation (Final) describes the evaluation of the interactive prototype '*InSituBoard*', which is designed to evaluate AML-model predictability in the context of expressive gesture typing (see D4.7 - Working Prototype and Designs (Initial)).

The objective of this deliverable is to better understand the capabilities of AML-based models for interactive systems. Our primary interest is to help users and the general public to engage in more creative expression with technology. This deliverable compares our previous work on Expressive Keyboards [1], with our AML-model based *InSituBoard* developed in D4.7 - Working Prototype and Designs (Initial). Expressive Keyboard is a smartphone application based on gesture typing, where, instead of tapping the keys of a soft keyboard, the user glides their finger from letter to letter to create words. The application explicitly captures individual variation of gesture, identifies different features of it and maps them to specific output, such as color variation.

However, this initial version [1] identified three distinct aspects based on simple heuristics of typing movements — speed, curviness, inflation, and acceleration — which were assigned to different colors. This enabled users to modify their visual expression while gesture typing by utilizing rich underlying information. In D4.7 - Working Prototype and Designs (Initial) we reported how we collected data from 12 participants over five days, tasking them to gesture-write according to their interpretation of 'calm' or 'exaggerated'. We aimed to capture this variation using our AML-model. We presented our findings from our evaluation with respect to the use case in deliverable D4.4 - Interaction Paradigm Methodology (Initial) and prototype in deliverable D4.7 - Working Prototype and Designs (Initial), which investigated new visualizations for human-AI explainability and controllability.

This deliverable begins by outlining *InSituBoard* and our previous work [1], which we used as a baseline. We then expand on the reasoning behind our chosen conditions, including the current limitation AML models and study setup. We describe the results of this final evaluation and discuss the implications of this work for expressive gesture typing.

2 Background

Recent studies on digital writing have increasingly utilized machine learning techniques to improve content recognition, such as predicting the most likely word based on context [2] and enhancing spelling or grammar [3]. These techniques are commonly integrated into both physical and digital keyboards, aiming to accurately predict user intent. Additionally, gesture keyboards have gained popularity, allowing users to input text by drawing a continuous line connecting letters, known as word-gestures [4]. Although these gestures can be matched using kinematic models and language models, the recognition engines often treat variations in gestures as noise, potentially overlooking the rich information they may convey, similar to handwriting.

In our previous work on Expressive Keyboards, we repurposed gesture-typing variations to create dynamic outputs like parametric text [1] and emojis [5]. Other research, such as TapScript [6], has also explored dynamic handwriting-like fonts based on touch-typing variations. However, a significant challenge remains in making gesture expression more explainable and controllable for users. Our exploration of user control over gesture features revealed that users were more successful in achieving desired output characteristics when focusing on the visual aspects of the output rather than explicit gesture instructions. To address this, we developed a prototype, *InSituBoard* (see D4.7 - Working Prototype and Designs (Initial)), that enhances dynamic human-AI interaction for gesture typing, enabling users to exert deliberate control over output characteristics while minimizing trial-and-error efforts.

In the following, we will provide a short summary of the two systems we compared in this deliverable. This information can be found in more detail in D4.4 - Interaction Paradigm Methodology (Initial) and D4.7 -

Working Prototype and Designs (Initial), but will be presented here as background for completion.

2.1 Expressive Keyboard

The Expressive Keyboards project introduces an innovative approach to gesture-typing, enhancing digital communication by transforming simple text input into rich, expressive outputs [1]. Traditional gesture-typing, while efficient, often fails to account for the natural variations in user gestures. This project aims to leverage these variations to allow users to control both the content and style of their text—such as dynamic fonts and colors—while ensuring text accuracy (see Figure 1).

The research is grounded in a heuristic framework, focusing on three key gesture features: curviness, typing speed, and inflation. Through three experiments, the project revealed that users naturally exhibit significant variation in their gesture-typing, which can be quantified and mapped to expressive outputs. Notably, users were more successful in achieving desired output characteristics when they concentrated on the visual outcome (e.g., "make it red") rather than the specifics of the gesture itself (e.g., "make it curvy").

In real-world applications, users found the Expressive Keyboard engaging and enjoyable, although they needed to adopt a trial-and-error approach to learn and explore different input gestures. Overall, the project highlights the potential of gesture-based interaction to enrich personal expression in digital communication, while also identifying challenges related to recognizing individual gesture variations.

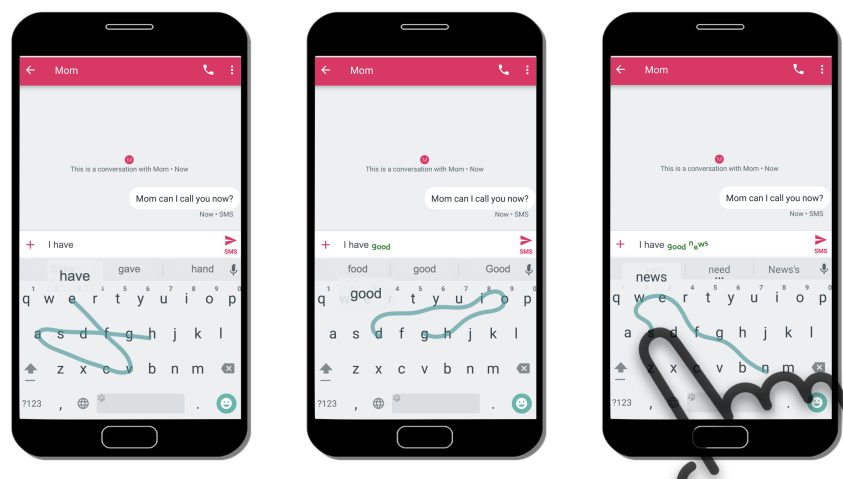


Figure 1: Examples for real world application of Expressive Keyboards

2.2 *InSituBoard*

In contrast to the expressive keyboard project, *InSituBoard* explored the potential for explainable creative expression through gesture typing. The application was built upon an AML-model that maps gesture input characteristics—specifically the writing situation (walking or sitting) and writing style (calm or exaggerated)—to expressive outcomes (for more details see D4.7 - Working Prototype and Designs (Initial)).

To enhance user experience, the project incorporated distinct visualizations using font and color styles, designed in collaboration with typeface designer Olivier Nineuil. Calm gestures are represented with blue hues, indicating stability and relaxation, while exaggerated gestures are depicted in red, symbolizing energy and passion. The intensity of these colors is influenced by the AML-model's confidence levels in recognizing the writing style.

The application operates on an LG Nexus 5 smartphone, utilizing an overlay keyboard that mimics a standard QWERTY layout. This setup allows for the collection of detailed gesture data, which is processed by the AML-model to predict writing styles and their corresponding expressive forms. The project aims to leverage these mappings and visualizations to guide users towards desired expressive outcomes while typing.

3 Study Methodology

We have designed a study to investigate the potential of AML-model prediction for situated typing using *InSituBoard* in comparison to the heuristic-based expressive keyboard. The goal of the study is to determine whether AML-based model compared to heuristic models improve 1) understanding of expressive gesture typing; 2) controllability of expressive gesture typing; and 3) make it more appreciated in everyday use.

3.1 Evaluating Conditions

In D4.7 - Working Prototype and Designs (Initial) we suggested to conduct a [3x2x2] experiment, using a within-participant design, followed by an open task to assess participants' preferences. The first factor (EXPLAINABILITY) was suppose to have three levels: baseline (no explainability); explicit explainability; and implicit explainability. The second factor (LOCOMOTION) should have two levels: sitting and walking. And finally the third factor (EXPRESSION) should have two levels: calm and exaggerated.

After experimenting with various levels of explainability, we observed that (a) gesture typing, (b) observing text changes, and (c) observing what explainability features predict about the these gesture and text changes was overwhelming the user. This became particularly clear since these three dimensions are inherently related. When a user slows down for better explainability, he or she would involuntarily also changes the text change patterns from fast to slow and may hold long enough to trigger an incorrect letter prediction. We thus decided not to include explainability visualizations in the final evaluation.

We also investigated the dimension expression (calm vs. exaggerated) and locomotion (sitting vs. walking) further. We observed that less than 60% accuracy for sitting and walking (see D4.7 - Working Prototype and Designs (Initial)) led to uncontrollable font changes. Instead, we chose to focus on the expression dimension, comparing the ability of AML to predict human intended expression to our previously published heuristic approach.

3.2 Participants

We recruited 8 participants (**3 men, 4 women, 1 undisclosed, ages ranged from 23–38 years**). Four participants had no experience with gesture typing, 2 tried but did not use it in their everyday life and 2 participants used it daily.

ID	Age	Gender	Educational Background	Gesture Typing Experience
P1	27	Female	Computer Science	None
P2	27	Female	Computer Science/ Medical Informatics	Tried/no usual use
P3	25	Female	Electrical Engineering/HCI	None
P4	23	Undisclosed	Graphic Design	daily user (Azerty keyboard)
P5	36	Male	Physics	No usual use
P6	38	Male	Computer Science	None
P7	32	Female	Computer Science	daily user
P8	28	Male	Computer Engineering	None

Table 2: Demographic and Gesture Typing experience of Participants

3.3 Setup

An Apple Macintosh laptop running the AML server for *InSituBoard* (described in D4.7 - Working Prototype and Designs (Initial)) was placed on a table. An Android phone running both applications was connected by cable to the laptop. The experimenter sat aside from the participant so that she could make pictures of the phone screens in a quick manner.

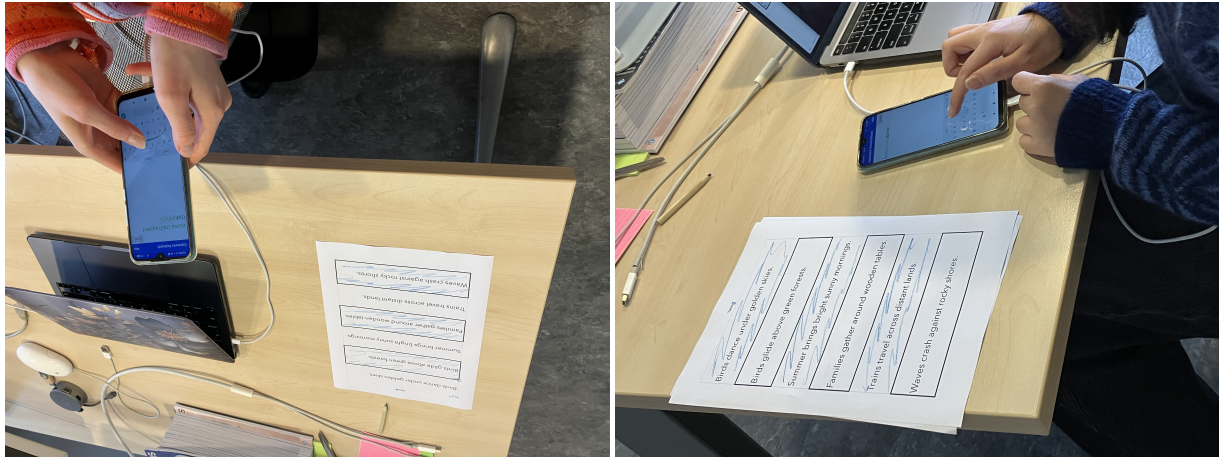


Figure 2: Setup Examples

3.4 Procedure

We conducted a comparative structured observation, comparing both expressive typing approaches, which lasted approximately 40 min. The session was organized as follows:

1. Introduction and consent form
2. Training phase: The user takes the phone provided and explores the gesture typing functionality on his/her own. This can take up to 3 min, until the participant feels comfortable to start the study.
3. First task/ first condition: The experimenter provides a page with the sentences to be typed and the aimed expression (calm or exaggerated) for each of these sentences. She further opens the application and the user starts typing the first sentence. After each sentence the experimenter makes a picture of the screen for later quantitative analysis. The user continues in the same manner with all 6 sentences.
4. Condition questionnaire: The user fills out an online questionnaire regarding the current condition and leaves comments regarding their experience.
5. Second task/ second condition: similar to the first one, the experimenter provides a page with the goal sentences but the aimed expression (calm or exaggerated) are reversed to avoid biases. The experimenter further opens another application with the second expressive gesture typing approach. Both application have the identical interface to avoid biases by the user.
6. Condition questionnaire: The user fills out an online questionnaire regarding the second condition and leaves comments regarding their experience.
7. Compare questionnaire: The user fills out an online questionnaire regarding their preferences and experiences with both condition and could leave comments.

8. Interview: The experimenter conducts a short interview regarding the participants experience with both conditions, expressed preferences and investigates the reason for these preferences. At the end demographic data were collected.

Conditions: We evaluated two levels of expression: *calm* and *exaggerated* using two different algorithmic approaches (heuristic and AML) using alternating tasks. Both approaches were implemented on an Android phone and used the same layout and keyboard to avoid user biases during the study. The heuristic-based approach run on the phone, while the AML-based approaches required the AML model to run on the connected laptop. To avoid biases, the phone was connected for both conditions to the laptop.

Tasks: We chose six sentences with five words each, with each word having between four and six characters. We made sure that each word was simple to type on a keyboard and focused on words that users would be familiar with. This was necessary to maintain sentence consistency while also allowing users to experiment with gesture typing across the keyboard. We provided the sentences on a piece of paper, which were highlighted based on the expression (calm or exaggerated) the user should aim for when writing them. To avoid preferences, the two tasks were counterbalanced.

The sentences were:

- Birds dance under golden skies.
- Birds glide above green forests.
- Summer brings bright sunny mornings.
- Families gather around wooden tables.
- Trains travel across distant lands.
- Waves crash against rocky shores.

3.5 Data collection

We collected both quantitative and qualitative data.

Quantitative data:

We recorded the output from the application during each step of each task by taking pictures. This allowed us to compute additional statistics, including number of correct words predicted, or number of intended expression correct predicted.

Qualitative data:

We audio recorded participants' descriptions of their thoughts and reflections after the study. We also collected their responses to the questionnaire and open-ended interview questions about their experiences with each approach, their level of control and their satisfaction with their results.

4 Results

We first report our results regarding the individual conditions and will follow with our insights based on the comparison of the two approaches.

4.1 Using AML-based expressive typing

We observed that AML-based expressive typing predictions were in 62% of the cases aligned with the users intent. This number raised to 73% for experienced users such as P4 and P7. Despite these differences, users rated both systems rather equal as shown in Figure 3, where we could identify no clear trend.

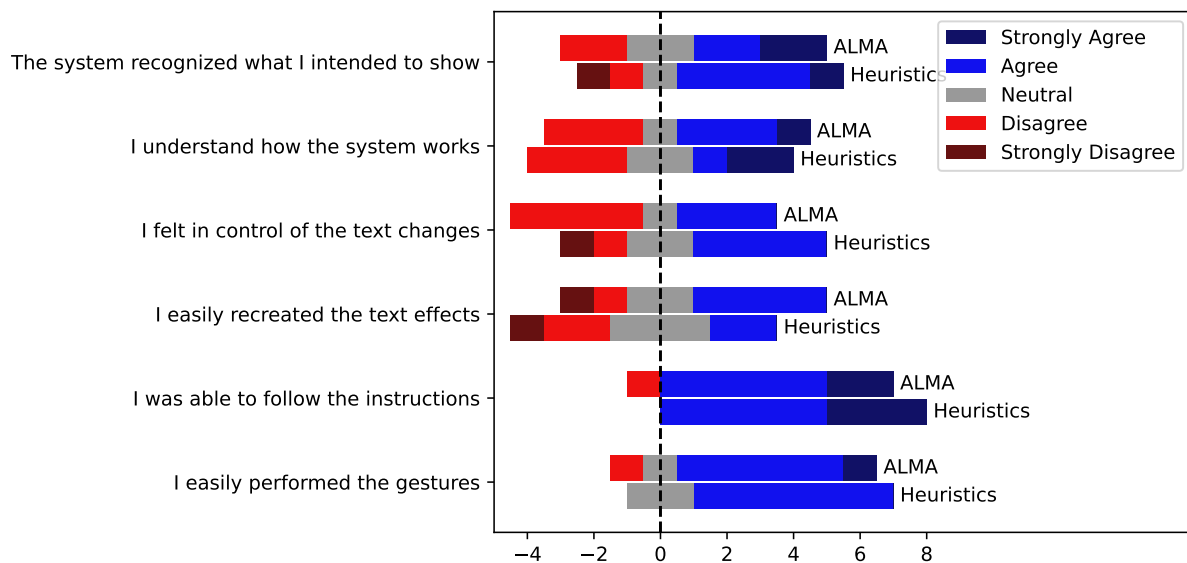


Figure 3: Results by condition

In our questionnaires regarding the AML condition, participants shared mixed but insightful feedback about their experiences with the gesture-typing system. P2 noted they understood the basic trend between colors like green and orange but struggled to see how their gesture speed influenced specific shades. They were surprised by the appearance of pink and expressed disappointment that the system didn't respond differently to their slow, wave-like gestures, which they intentionally created to mimic crashing waves. P3 felt they typed faster and more fluid than in heuristic condition but still had difficulty typing the word "shores" correctly. P4 attributed some of their struggles to being unfamiliar with QWERTY keyboards (as they typically use AZERTY), which made it harder to gesture quickly and accurately. They noticed text effects like colors but were more focused on speed and following instructions, though they speculated that colors might relate to speed or mistakes.

P6, a first-time user of gesture-typing, found the experience challenging due to their lack of familiarity. They had to focus heavily on the keyboard, which limited their ability to observe text changes. However, they were pleasantly surprised by the system's accuracy in recognizing their intended text, which left them feeling optimistic about using such interfaces in the future. P7 felt the trial was too short to fully grasp the system's potential, suggesting they would need more time to explore and understand its functionality.

To summarize, participants highlighted challenges related to unfamiliarity with gesture-typing and keyboard layouts, as well as difficulties in balancing speed, accuracy, and observing system feedback. However, many expressed optimism about the system's potential, particularly its accuracy and the engaging nature of its expressive outputs.

4.2 Using heuristic-based expressive typing

The heuristic-based expressive typing predictions revealed a different pattern compared to the AML-based approach. It was only in 53% of the cases aligned with the users intent, which is close to chance. We also saw a strong difference in the heuristics ability to predict quick/fast writing in particular. This number only raised to 66% for our experienced users (P4 and P7).

This was also reflected in the participants feedback. P7, a highly experience gesture typist for example expressed frustration, stating that the system didn't understand their gestures. P6 on the other hand, felt more accustomed to gesture-typing over time and could focus better on typing itself, which point to potential familiarity biases. They found the color feedback mysterious and somewhat inconsistent, with orange words appearing rarely, but sensed that the system was trying to communicate something. They concluded that more practice would be needed to fully understand it.

P4 found the color palette intriguing and tried to interpret its meaning, feeling it was unrelated to errors. They also noted feeling more familiar with the QWERTY layout during this task (second condition), despite typically using AZERTY, and appreciated the real-time text display as they typed. P3 acknowledged occasional difficulties in typing the correct characters but felt they typed faster overall, especially with more common words. P2 identified trends in color changes and experimented with gesture speed to influence color transitions, though they couldn't consistently recreate the effect or determine how pauses between words affected the colors.

Finally, P1 described the initial challenge of coordinating gestures while simultaneously checking for accuracy, particularly during the fast-typing condition. This dual focus made the task difficult at first, highlighting the learning curve associated with the system.

Overall, participants expressed subtle differences between the two gesture typing approaches despite presenting rather different error patterns as shown in Figure 7

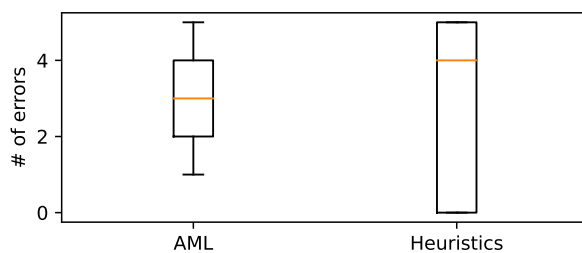


Figure 4: Error rates by condition

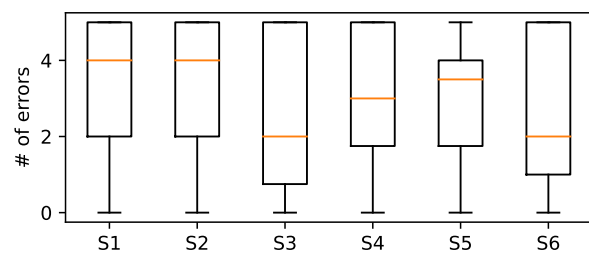


Figure 5: Error rates by sentence

Figure 6: Error rates

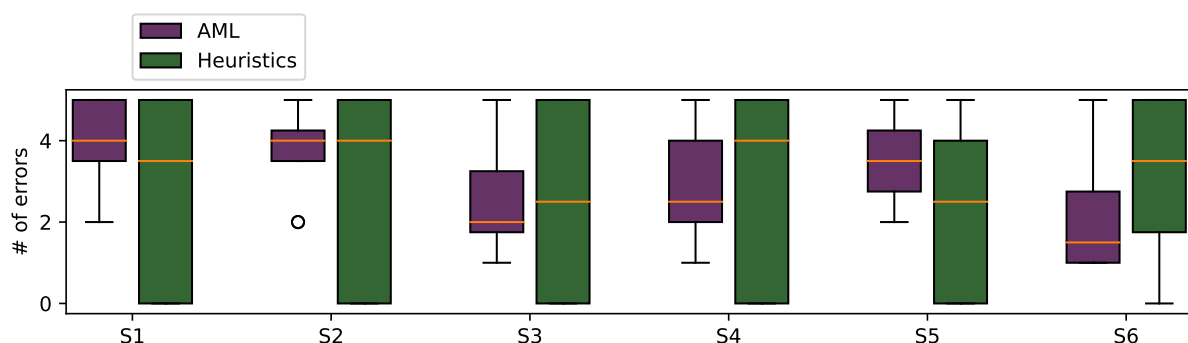


Figure 7: Error rates by sentence and condition

4.3 Comparing AML-based and heuristic-based expressive typing

After the study, participants reflected on their use of the two conditions through a questionnaire and a short interview. Our quantitative results shown in Figure 8 show that despite small differences, users experienced more control and felt more competent to steer the application to produce the outcome they intended. Our thematic analysis reveals a trade-off between speed, control, and expressiveness in the two conditions. The AML approach was often favored for its efficiency and predictability, making it suitable for fast and casual typing. On the other hand, the heuristic approach, while sometimes harder to interpret, is perceived as more informative and expressive by certain users. In the following, we outline the main themes that emerged from the interviews in more detail.

4.3.1 Perceived Control and Understanding

A recurring theme across participants' responses is the sense of control and understanding over how the system behaves. Participants who used the heuristic approach reported challenges in understanding the logic behind color changes. For instance, P2 mentioned, "In the second one [heuristic] I sometimes didn't know why a color came up." Similarly, P6 noted inconsistencies in the heuristic system, observing that it sometimes displayed unexpected colors such as "black or bright pink." P8 also remarked, "I did feel in the second condition [heuristic] I had more control." In contrast, the AML approach was seen as more predictable and interpretable by several participants, with P1 expressing a greater sense of control in the first trial using AML: "I had the feeling in the first trial [AML] I controlled it a little bit, but in the second one [heuristic] I didn't feel that." P5 echoed this, stating, "I think in the second situation [AML] it was interpreting in the best way my intention." However, some discrepancies were noted in AML's consistency, as P8 observed, "In the first condition [AML] I saw that it was some kind of color coding that slow is more green and fast is more red, but sometimes that didn't work."

4.3.2 Preference for Speed and Efficiency

Many participants favored the AML approach for its efficiency, particularly in daily use. P1 stated, "For the daily use the second one [AML], because it is faster." This aligns with P3's perspective: "I feel like for me the latter approach [AML] is somehow faster and I feel like I performed better, like my typing is better and more accurate than in the first one [heuristic]." P5 also leaned slightly toward AML, noting, "Maybe a slight advantage for the second [AML]." Additionally, P3 noted that the faster task encouraged fluid and rapid typing: "I think generally I preferred the faster tasks. Also, the gesture typing was encouraging to type faster and faster." P4, however, expressed concerns about the AML system's color feedback: "The first one [AML] had this color palette that went from green to orange to red, and I didn't know if it was because I was making errors or because it was only because of my speed."

4.3.3 Ease of Use vs. Expressiveness

While AML was often preferred for its speed, the heuristic approach was sometimes perceived as more expressive or informative. P6 described heuristic feedback as more visually engaging: "The second system [heuristic] seems to be more informative." P8 also found the heuristic system more consistent: "I preferred the second condition [heuristic] because I felt the system was more consistent with what I was expecting." However, some users found the heuristic system harder to control or understand. P2 observed that "In the second condition [heuristic] it seemed almost like the length of the break before I started writing a new word was influencing the color." P4 echoed this sentiment, stating, "The second one [heuristic] [...] I thought it was just a color palette that makes sense of something, I don't know why or what." This unpredictability made some users hesitant about its everyday usability.

4.3.4 Desire for Personalization and Interpretation

Several participants expressed a need for clearer explanations or more customization options. P8 stated, "I would be interested to use it [in everyday life], maybe I would like to have more control or understanding on what it is doing and how I can manipulate it in the way that I want to express myself." This sentiment was echoed by P7, who suggested a more direct visual application: "What I would prefer is something that is more a direct application of the actual shapes that I put in. For example, if you took those actual strokes and would convert them into an abstract background of the text, that might work a lot better for me." P6 also wanted more transparency in the system's operation: "I wanted to have more visible feedback during typing, whether the system is actually recognizing what I want to say, not as a final result." Additionally, P2 played around with speed variations and noted, "I think I preferred my number one [AML] with my first condition writing slow because it created different hues of the same color."

4.3.5 Situational Usability and Social Considerations

Participants highlighted different contexts where each system might be preferable. P2 expressed concerns about disclosing typing speed, stating that "sometimes you want to tell someone 'hey I have written this message – I thought a lot about it – and I took a long time to draft it' and sometimes you don't want to show it." Similarly, P3 linked the AML system to casual settings: "For a quick response to a friend or for casual settings, I think the faster one really allows me to express myself."

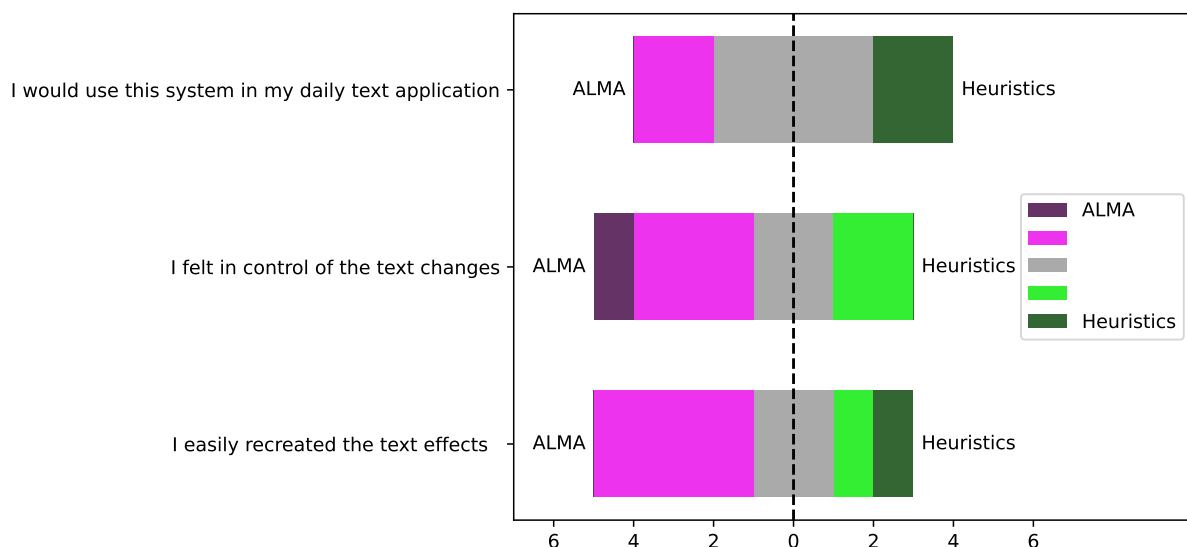


Figure 8: comparing conditions

5 Discussion and Summary

The goal of this deliverable was to evaluate our prototype designed and described in D4.4 - Interaction Paradigm Methodology (Initial) and D4.7 - Working Prototype and Designs (Initial). Our study examined two approaches to expressive typing: AML-based and heuristic-based systems. The AML-based approach demonstrated a higher alignment with user intent, achieving 62% overall accuracy, which increased to 73% for experienced users. Participants generally found the AML system more efficient and predictable, leading to a greater sense of control and competence in typing. Many users appreciated its speed, noting that it encouraged fluid and rapid typing, making it suitable for casual use.

In contrast, the heuristic-based approach only aligned with user intent in 53% of cases, with a slight improvement to 66% for experienced users. Feedback indicated that users found the heuristic system less predictable and harder to interpret, which sometimes led to frustration, which was supported by our quantitative analysis 7. However, some participants found it visually engaging and more expressive, suggesting it could provide informative feedback despite its inconsistencies.

5.1 Limitations

This study illustrates the feasibility of developing an interactive AML application for creative purposes and the advantages derived from the interpretability of the atoms in AML. The objective was to evaluate the relative efficiency of AML models against established and documented approaches in HCI. Despite the limited number of participants, our evaluation has demonstrated the advantages of employing the AML approach. Larger studies, including qualitative as well as quantitative methods, are necessary to fully assess the advantages and challenges linked to the AML approach in machine learning for these applications. We compared the AML approach solely to one heuristic approach. Additional studies are required to investigate the advantages of AML when compared to other ML models. Enhanced explainability measures may further clarify the advantages of AML compared to other ML methodologies.

5.2 Summary

The objective of this deliverable, D4.11 - Evaluation (Final) is to evaluate our previously produced prototype for applying AML models in creative applications. This work expands upon the design work reported in D4.4 - Interaction Paradigm Methodology (Initial) and the prototype detailed in D4.7 - Working Prototype and Designs (Initial). We compared the AML-based gesture method of *InSituBoard* to our prior work on Expressive Keyboards using a comparative structured observation approach with 8 participants of different levels of experience with gesture typing. Our qualitative and quantitative results found noticeable and important differences, favoring the AML-based approach.

Participants preferred the AML technique because it was efficient and predictable, making it ideal for fast typing and casual discussion. The heuristic technique, while more difficult to understand, was seen as possibly more expressive, emphasizing the trade-off between speed and expressiveness. In the future, more research is needed to better understand the explainability potential of AML and compare it to other machine learning models.

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