



Human-centric algebraic machine learning

## Human-AML Interaction - Final

Deliverable D4.3

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 D4.3 - Human-AML Interaction - Final* of the ALMA project. The goal of this deliverable is to provide a state-of-the-art review of the literature incorporating research from the cognitive and social sciences as well as research in information visualization.

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## Acronyms

**AML** Algebraic Machine Learning.  
**IML** Interactive Machine Learning.

# 1 Introduction

The goal of this set of deliverables is to provide a state-of-the-art review of the literature incorporating research from the cognitive and social sciences as well as research in information visualization. This deliverable aims to give insight into current research on making interactive systems more accessible to end-users through direct and indirect feedback and their visualizations. While there are a number of factors involved in educating and empowering end-users of machine learning applications like AML, we focus in this deliverable D4.3 - Human-AML Interaction (Final) mainly on direct and indirect means of explainability applied in current tools to increase the usefulness of machine learning in creative practice, as well as how to study those.

The field of Human-Computer Interaction (HCI) has increasingly focused on co-creative systems in music, where artificial intelligence (AI) and human creativity intersect to generate novel artistic experiences. Co-creative systems empower users by facilitating dynamic interactions, enabling them to shape and refine musical expressions with computational assistance. However, the effectiveness and engagement of such systems often depend on the clarity of their contributions and the methods used to explain their decision-making processes. Understanding these "means of explainability"—which encompass both direct outputs such as sounds and supporting explanatory elements like visuals, chord structures, or similar techniques—is crucial in enhancing user experience and engagement in co-creative music systems.

The previous deliverables D4.1 - Human-AML Interaction (Initial) and D4.2 - Human-AML Interaction (Revised) focused mainly on the interaction between human and machines and discussed the underlying concepts such as *Grounding* and *Theory of Mind* as well as the interaction paradigm we applied to make AML more accessible is *Interactive Machine Learning* (Interactive Machine Learning (IML)) allowing users to gradually train a model through interaction on a particular task. In D4.2 - Human-AML Interaction (Revised) we further highlighted the role of end-user participation in machine teaching to enhance model understanding and applicability. We concluded with the growing importance of interactive approaches for ML literacy amid the rise of everyday ML applications.

In this deliverable, D4.3 - Human-AML Interaction (Final), we report on a systematic literature review to investigate the diverse methods employed to explain and contextualize the contributions of co-creative systems in music. Our review encompasses a broad spectrum of topics, including AI-driven co-creative systems for music, AI agents, and their interactive mechanisms. We explore how these systems employ various means of explainability to support user understanding and engagement, ranging from auditory feedback to multimodal representations.

To summarize, we will first introduce our methodology to identify the reviewed literature (section 2), before outlining the results in the following sections. We will highlight how these insights can help better understand the role of explainability for collaborative AI in the context of creative practice (section 5).

## 1.1 Motivation

We turned to co-creative musical systems as an anchor point for our literature analysis as (1) we expanded the use of AML in co-creative music practice in several of our deliverables, and (2) as they can be characterized by their ability to facilitate a collaborative creative process between humans and machines, where both parties contribute to the generation and manipulation of musical content. This provides a great starting point to investigate explainability means and how they can be used in co-creative systems such as our AML applications.

Qualitative evaluation by humans plays a crucial role in assessing the effectiveness of musical systems. Human evaluators, often music experts, provide valuable insights into the musicality and aesthetic quality of the generated content. Co-creative musical systems further have to address the challenges of AI-

induced information overload and non-deterministic outputs. Users often face difficulties in understanding how these systems make decisions and contribute to the creative process. Therefore, it is essential to develop means of explainability, including direct outputs and supporting visual elements, to improve user experience and foster a more intuitive interaction with the system [1].

In summary, co-creative musical systems have shown significant advancement in the last years. By leveraging AI and computational methods, these systems enable users to engage in a dynamic and interactive creative process. The effectiveness of these systems relies on clear explanations of their functionalities and decision-making processes, as well as the development of visualizations and other tools to support user understanding. As the field continues to evolve, addressing the challenges and opportunities in enhancing explainability will be crucial for the widespread adoption and success of co-creative musical systems, which is the aim of this review.

## 2 Research Method

We conducted a comprehensive literature analysis on intersection of co-creation, music technology, and AI agents. We performed a structured search using the digital library Semantic Scholar. The search focused on peer-reviewed research articles published within the past five years. The inclusion criteria required papers to be related to artificial intelligence (AI) and music, emphasizing co-creative systems, collaborative interactions, and AI agents.

### 2.1 Identification Process

#### 2.1.1 Semantic Scholar Search

We applied filters restricting results to the ‘past five years’ within the fields of ‘Computer Science’ and ‘Arts’, with a minimum ‘citation count of 10’. The search process involved multiple queries designed to capture a broad yet relevant set of research works. The following search terms were used, and results were refined accordingly:

- **“Co-creative system ‘music’”** yielded 22 papers. We retained 13 after excluding background music (1), game design (1), non-interactive works (2), music generation from text (2), machine learning (1), redundant entries (1), and education-related papers (2).
- **“Music collaboration”** returned 5 papers. We retained 4 and one was inaccessible.
- **“Music” collaborative system** produced 10 papers. We retained 9 retained after filtering duplicates (1), inaccessible papers (1), and music generation papers (1).
- **“Music” AI agents** initially identified 32 papers, with 20 remaining after removing duplicates (5), studies on Large Language Models (LLMs) (2), music perception (2), blockchain (1), course descriptions (1), inaccessible papers (1), and education-focused studies(4).
- **“Music” AI** retrieved 5 papers, all of which were excluded due to duplication (4) or irrelevance (1, a review on studying games).

### 2.2 Data Processing and Refinement

Following the search and filtering process, the selected papers were systematically analyzed for their relevance to co-creative AI systems in music, focusing on methodologies, technical implementations, and contributions. Papers that lacked direct relevance, were duplicates, were inaccessible, or focused solely on recommendation systems or unrelated AI applications were excluded.

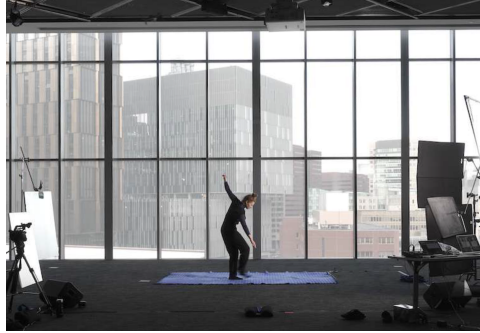


Figure 1: The Tapis Magique installation and performance [2].

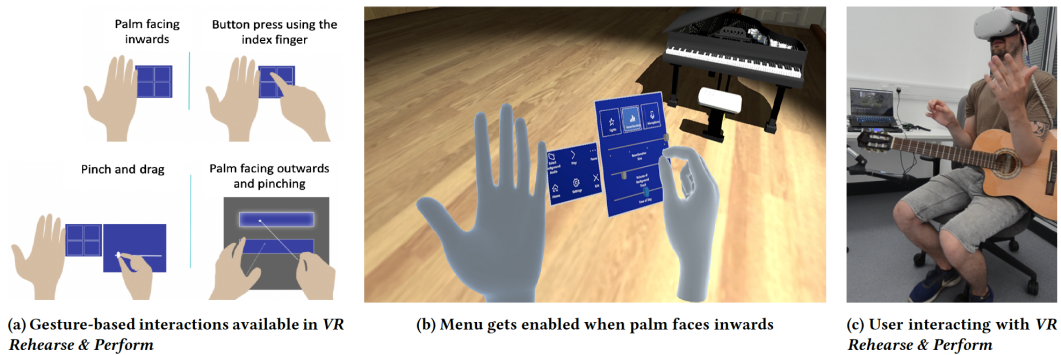


Figure 2: Overview of interaction with VR Rehearse &amp; Perform [3].

This structured approach ensured a focused dataset of literature that directly contributes to understanding AI's role in interactive and collaborative music systems, highlighting key trends and gaps in current research.

### 3 Direct Forms for Explainability

#### 3.1 Visual and Auditory Feedback

Recent work reveals that providing visual and auditory feedback affects users' interaction with the system [2, 3, 4]. In particular, Wicaksono et al. [2] have shown that using a visual and auditory feedback strategy for explainability is successful with dancers and sound artists providing them with new creative opportunities where they retain agency and intimacy, while still improvising within a choreo-musical performance by the Tapis Magique textile interface (see 1). Tapis Magique is a large-scale electronic textile carpet that is pressure-sensitive and knitted. It generates an immersive sound environment in real-time based on the dancer's body location, postures, and gestures. Another project by Ppali et al. [3] showed that using a visual and auditory feedback strategy for explainability is also successful with musicians and performance experts, since it can offer them support when rehearsing, performing or improvising in their creative workflow. They began by gathering musicians' needs and then created a music-centered VR system called VR REHEARSE & PERFORM that transports musicians into a new acoustic and visual spaces that reflects those needs. Furthermore, Li et al. [4] showed how using a visual explainability strategy can also successfully produce long sequences of realistic dance movements. Fig. 3 shows how the input music from /textscFACT, a Full-Attention Cross-modal Transformer network for generating

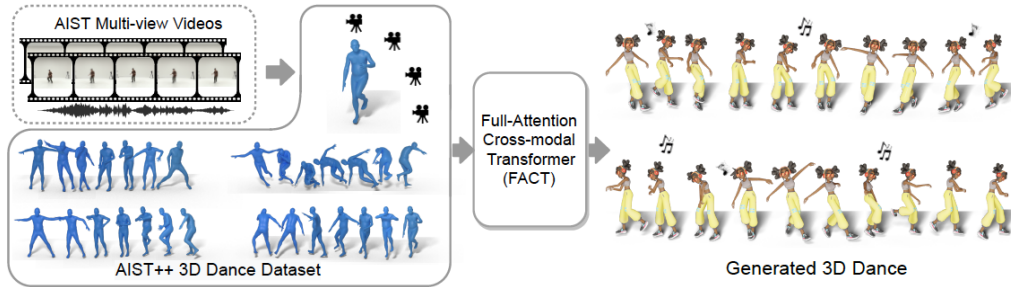


Figure 3: Pipeline of Li et al.'s AI choreographer [4].

3D dance motion conditioned on music, can be tuned to address the musician's requirements.

## 4 Indirect Forms of Explainability

### 4.1 Visual and auditory Feedback

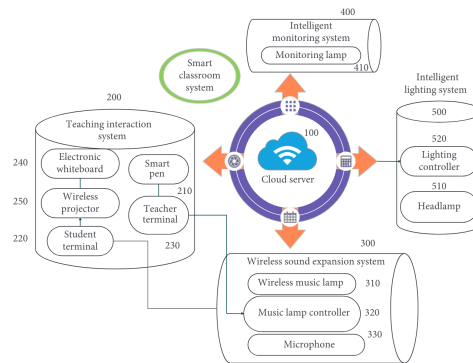


Figure 4: The AI based Multimedia-assisted music teaching system [5].

Recent work shows that providing visual and auditory feedback affects the users' interaction with the system [5, 6]. Specifically, Ma [5] showed that using a visual or auditory feedback strategy for explainability can also successfully support music teachers as they attempt to improve modern music education. They propose a multimedia-assisted music teaching system based on AI technology (see Fig. 4) that includes smart classrooms, musical instruments, auxiliary teaching programs, analyzes students' activity and performance data in music classes, and provides feedback information.

Finally, Deruty et al. [6] showed that using audio-based AI tools is better aligned with the production of contemporary popular music creative processes than purely piano-roll/MIDI-based tools. They show the importance of symbolic representations and how to integrate composition with editing and mixing.

### 4.2 Interactive Learning and Co-Creation

Recent research has demonstrated that interactive learning and co-creation feedback can significantly enhance users' engagement with co-creative music systems [7, 8, 9, 10, 11, 12, 13, 14, 15]. For example, Louie et al. [7] revealed that novice composers benefit from a suite of AI-steering tools—ranging from



Figure 5: Truchet et al.'s smart guitar system [8].

content generation restrictions and similarity control to nudging musical direction (e.g., happy/sad, conventional/surprising) and auditioning diverse AI-generated options—which in turn fosters higher levels of trust, control, understanding, and a sense of collaboration and self-efficacy.

Research with musicians further supports these findings. Turchet and Barthet [8] demonstrated that guitarists and electronic music performers experienced positive emotional engagement through a ubiquitous smart guitar system that facilitated collaborative practice between a guitarist and a smartphone (Fig. 5). Similarly, Bernardo et al. [9] found that professionals developing music software enjoyed an intuitive and fun learning process when using interactive machine learning via the RAPID-MIX API.

Evidence from educational contexts also underscores the impact of these strategies. Wang [10] reported that 82% of music majors preferred an AI-based vocal teaching system over traditional methods, noting its potential to support independent learning while enabling teachers to monitor progress through analytical reasoning. Complementing this, Yan [11] showed that an online music education system that integrated a SCMA multi-user detection algorithm with artificial intelligence (Fig. 6)—not only improved students' learning efficiency but also offered comprehensive support from features such as information management and curated music exercises and courses. NG et al. [14] extended these findings to address younger learners: they illustrated how a flipped classroom model that used the MUYU application effectively motivates secondary school students in Hong Kong to engage with and learn folk-talk-singing traditions.

Various researchers have demonstrated how the versatility of interactive co-creation positively affects creative and design contexts. Banerji [12] examined how improvisers benefit from reconfigured methodological approaches in the MAXINE improvising system for evaluating interactive musical meta-creation. Zhang et al. [13] introduced the LOOP COPILOT system—a multi-round dialogue interface that enables users to iteratively create and refine music.

Kayacik et al. [15] also described their *PAIR Bungee* program which embeds UX designers into ML research groups as an effective approach for bridging the between design and technical expertise. Their results showed how a human-centered perspective can enrich machine learning projects. Finally, Suh et al. [16] showed that when musicians compose in pairs with with AI, they shift between collaborative and creative roles, with a corresponding reduction in interpersonal friction, enhanced group progress, and the creation of a psychological safety net that encourages creative risk-taking.

### 4.3 Recommendation-Based Feedback

Recent studies have shown that recommendation-based feedback can profoundly influence how users interact with music systems [17, 18, 19, 20, 21, 22, 23, 24, 25, 26]. They describe a variety of approaches,

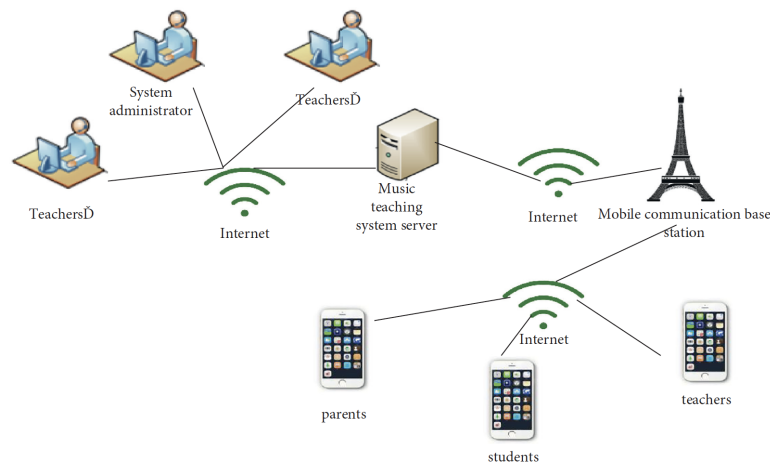


Figure 6: System diagram of Yan et al.'s online music education system [11].

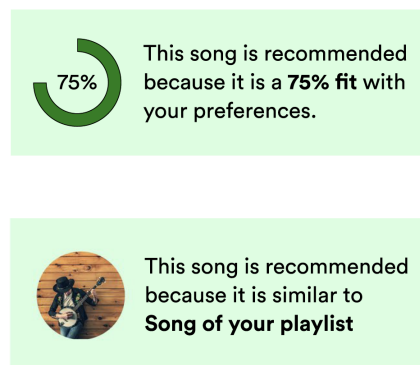


Figure 7: Example of adapted explanations from [21].

ranging from hybrid recommendation systems to blockchain-based models, each addressing unique challenges and user needs.

For example, Fessahaye et al. [17] developed the TUNES RECOMMENDATION SYSTEM (T-RECSYS), which combines content-based and collaborative filtering to power a deep learning classification model. When tested on SPOTIFY, the RECSYS CHALLENGE data achieved an 88% precision score at a balanced discrimination threshold by delivering accurate, real-time recommendations. However, in a related study, Paul and Kundu [18] cautioned that no recommendation system is perfect and that even promising hybrid approaches still raise significant challenges.

In the realm of music education, Tang and Zhang [19] demonstrated the effectiveness of a personalized recommendation algorithm integrated with a deep belief neural network. Their decision support system leveraged matrix decomposition of user ratings through a hidden semantic model, which then extracted both preferences and music weights, as well as audio features from music clips. Bhaskaran and Marappan [20] reported similar success with e-learning platforms, where content-based filtering enhanced recommendation accuracy for students. Martijn et al. [21] went further by adapting explanations in music recommender systems that matched users' personal characteristics (see 7). Similarly, Kim et al. [22] demonstrated a mobile application that predicts users' emotional preferences and delivers corresponding

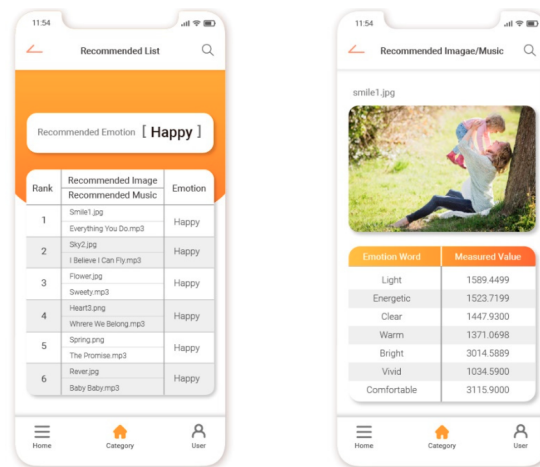


Figure 8: Predicted emotional preferences from Kim et al.'s application [22].

recommendations (see 8). Lyu and Wang [23] extended these findings by implementing an intelligent classroom teaching system that equips teachers with robust design tools and provides students with appropriate content.

Conversational interfaces can also play an important role in enhancing the user experience. Nair et al. [24] introduced an emotion-based music recommendation system where users interact with a chatbot to receive curated playlists (see 9). Schedl et al. [25] contributed to the field by releasing the expansive LFM-2B dataset, which underpins context-aware recommendations that consider both mood and situational factors.

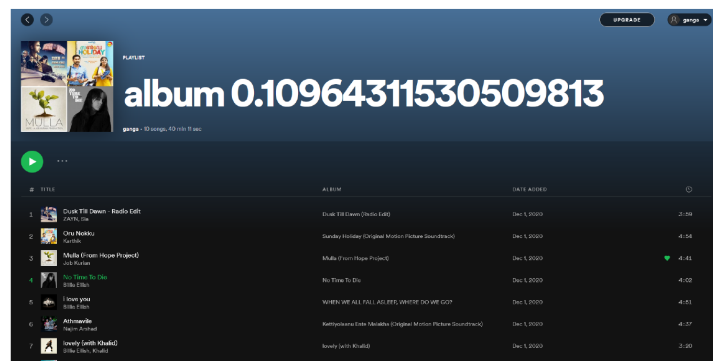


Figure 9: Curated playlist for a sad mood, from Nair et al.'s chatbot [24].

Other studies highlight emerging innovations and their corresponding trade-offs. Singh [27] noted that while recommendation-based strategies can improve accuracy, they may also lead to the recommendation of less-favored music. Boughanmi and Ansari [28] demonstrated that a multimodal machine-learning framework can generate contextual recommendations capable of predicting the success of musical albums and playlists. Hong et al. [29] employed the FUZZY ANALYTICAL HIERARCHY PROCESS (FUZZY AHP) to evaluate the role of AI and ML in music education, providing a robust decision-making framework based on multiple criteria.

Emerging technologies further expand the scope of recommendation-based strategies. Li [30] proposed

a novel blockchain model that treats music files as NONFUNGIBLE TOKENS (NFTs), thereby activating smart contracts and effectively securing copyrights while delivering recommendations. Zhao et al. [31] pointed out that advances in AI are affecting primary school music teachers' key competencies and professional development, indicating a need for improved educational management systems. Meanwhile, Xiao et al. [32] explored how concept creation methods relate to varying kinds and levels of conceptual representations. Finally, Morreale [26] raised concerns that AI-driven innovations might threaten traditional musicians by capturing audience attention on major platforms, and argued that such innovations are ideologically rooted in neo-colonialist practices that exploit user data and existing music for profit-driven purposes.

## 5 Discussion

This literature analysis highlights the significance of explainability in co-creative music systems, in both its direct and indirect forms. The insights gathered from these recent studies suggest that visual and auditory feedback, interactive learning, and recommendation-based strategies all play a crucial role in shaping user experience, engagement, and creative agency within these systems.

One key takeaway is the effectiveness of VISUAL AND AUDITORY FEEDBACK in fostering meaningful interaction. A number of studies demonstrate that real-time visual and sonic representations improve users' ability to interpret system behavior, enhancing their control, trust, and engagement. Specifically, projects such as TAPIS MAGIQUE [2] and VR REHEARSE & PERFORM [3] illustrate how such feedback mechanisms support improvisation and performance in creative workflows. Similarly, AI-driven dance motion generation through FACT [4] showcases how explainability aids in producing coherent, expressive outputs. These findings underscore the necessity of designing feedback mechanisms that align with user expectations, artistic intent, and workflow requirements.

The role of *interactive learning and co-creation* further strengthens the argument in favor of enhanced explainability in AI-powered music systems. AI-assisted composition tools, such as those explored by Louie et al. [7] and Zhang et al. [13], indicate that musicians and composers benefit from guidance mechanisms that help steer creative decisions without undermining artistic autonomy. Additionally, systems tailored for educational contexts, including AI-driven music teaching [10] and flipped classroom models [14], emphasize how explainability fosters learning efficiency, motivation, and self-efficacy. These studies suggest that co-creative systems must integrate adaptable, intuitive explainability features that cater to users of varying expertise levels.

The IMPACT OF RECOMMENDATION-BASED FEEDBACK extends beyond mere personalization, influencing how users engage with AI-generated musical suggestions. Research in this domain reveals that hybrid and content-based recommendation models improve system usability by tailoring outputs to users' preferences. However, studies also caution against over-reliance on algorithmic suggestions, as it may lead to biases in creative exploration [18]. Emerging approaches, such as blockchain-integrated recommendation models [30] and AI-driven contextual awareness [25], highlight the evolving landscape of explainability and the need for transparent, user-aligned strategies.

Despite these advances, several challenges remain. Explainability in co-creative music systems must balance INTERPRETABILITY AND COMPLEXITY, ensuring that feedback mechanisms are neither overly simplistic nor overwhelming. Moreover, ethical concerns, such as data privacy, AI bias, and the potential displacement of traditional musicians [26] necessitate further discussion concerning responsible AI practices. Additionally, the COGNITIVE LOAD associated with interpreting AI-generated suggestions should be carefully managed to prevent creative bottlenecks.

## 6 Conclusion

The goal of this deliverable D4.3 - Human-AML Interaction (Final) is to provide background and context related to recent studies that have investigated the roles of explainability and visualization on co-creative systems, especially how to increase end user usability.

This review of the literature shows that integrating explainability in co-creative music systems can significantly enhance user interaction, trust, and creative agency. Future research should explore *multimodal feedback strategies*, *adaptive learning models*, and *user-centric AI design* to further refine these systems. By addressing existing challenges and embracing an interdisciplinary approach, co-creative music systems can evolve into more transparent, inclusive, and empowering tools for musicians, educators, and artists alike.

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