From Me to We: Shared Multi-User Personalized Experiences in Smart Environments

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Abstract

Personalized experiences within single-user applications have become ubiquitous, yet when multiple people share a physical space, smart environments are either made to adapt to individual user preferences or to stereotypical predefined groups. Hence, mechanisms and design principles are needed to blend and share individual preferences. In this paper, we propose a multi-user music playback scenario and prototype a decentralized application that combines Solid Pods to store users' music and sharing preferences, and a Mixed Reality application that enables users to blend individual preferences into a collective music experience using smart speakers. We take this exploratory scenario to suggest relevant design dimensions to consider when creating solutions for shared multi-user personalized experiences in smart environments.

CCS Concepts

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**; **Mixed / augmented reality**; • **Information systems → Personalization**.

Keywords

smart environments, multi-user personalization, music recommendation

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1 Introduction

Personalized experiences in single-user applications are increasingly becoming ubiquitous [27], including in smart environments such as smart homes [7], industrial shop floors [9, 29], or museum experiences [22], where interactions with physical objects and devices are tailored to individual users. The recommendation algorithms that enable these experiences are optimized for individual engagement, thereby reducing content diversity [17]. Specifically in music, Anderson et al. [3] found that on Spotify, algorithm-driven listening is consistently associated with reduced diversity compared to users' own discovery, and that users that change their consumption over time, do so by moving away from algorithmic recommendations. Shakespeare et al. [26] found through a large analysis that even when algorithms appear to broaden users' exposure to diversity, it remains shallow, for example by recommending to a user an artist they have not heard before, but within their preferred genres. While research on group recommender systems studies personalization algorithms that take the preferences of multiple people into account [2, 8], these algorithms are often examined without considering the physical and social context in which the personalized content is eventually experienced. In shared physical environments, individuals with different tastes must negotiate a single collective experience. Existing commercial solutions such as Spotify Blend[1] automate this by combining users' taste profiles into a shared playlist, but are made for asynchronous, remote experiences with little control over how data is shared.

We present *WeMix*, a decentralized prototype that instead treats taste blending as an explicit user-controlled interaction, allowing users to select from three blending methods. *WeMix* combines individual Solid Pods [23] that store users' music preferences, and sharing preferences, with a Mixed Reality (MR) application that enables co-located users to create a shared playback music experience on a smart speaker. Based on our experiences in ideating and developing *WeMix*, we identify design dimensions to consider when creating solutions for multi-user personalized experiences in smart environments.

2 Related Work

Music is one of humanity's oldest mechanisms for social bonding. Savage et al. [24] argue that musicality (the biological set of capabilities that allow humans to perceive and create music) is a characteristic that co-evolved with human sociality, and that active musical behaviors such as synchronization (moving in time with others) and harmonization (sounding in tune together) serve to

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[1] https://support.spotify.com/us/article/social-recommendations-in-playlists/. Last accessed June 3rd, 2026

create and reinforce social bonds. Boer [5] found that shared music preferences serve a social bonding function that operates independently of cultural background, making it a nearly universal human phenomenon. However, the personalized content paradigm of today's services (including music, social media, and entertainment) works against this social dimension.

Music streaming platforms have begun to acknowledge this gap; they enabled the creation of Collaborative Playlists (CPs), allowing multiple users to contribute tracks that reflect their individual tastes. Through a large-scale survey, Park and Kaneshiro [18] show that social motivations (e.g., bonding, identity expression, and discovering others' tastes) are at least as important as curated music. Furthermore, factors such as group size, purpose, and listening context significantly impact how people participate in the curation of a CP. The companion paper [19] highlights that user engagement in CPs deteriorates when disagreements about content go unresolved, or when users feel their contributions are ignored due to social frictions and platform limitations. These studies show that the social aspects of group curation matter as much as the technical means.

Regarding automated curation of music, MusicFX [15] is an early example. Deployed in a fitness center in 1998, it automatically played music based on the aggregated preferences of the individuals physically present, without giving them direct control over the playback. The closest contemporary equivalent to this collective automation is Spotify Blend, which automatically generates a shared playlist by combining the distinct music tastes of a group. Kwak et al. [13] found that among Spotify Blend users, particularly among those who already knew each other, Spotify Blend promotes unspoken mutual understanding and indirect forms of communication (e.g. playing a song they would like that Blend adds to the playlist), demonstrating prosocial behaviors.

However, both MusicFX and Spotify Blend treat preference aggregation as an automated and opaque process. CPs give users explicit control, but are designed for asynchronous remote interaction rather than shared physical space. *WeMix* sits at the intersection of these two lines of work; allowing co-located users to actively and transparently negotiate a collective music experience.

3 *WeMix*: A System for a Multi-User Music Playback Experience

WeMix aims to address everyday scenarios. Consider Tina, who lives with her boyfriend Oliver and her flatmate Whitney. Tina installed a smart speaker in the living room and has configured it with her own music streaming account. Oliver uses the smart speaker (hence Tina's account) as if it were his own. On her side, Whitney is authorized to use the speaker, but is advised not to use Tina's account, since they do not share the same taste in music. Next week, Tina is celebrating her 28th birthday with a big party, she is inviting friends from different parts of her life (e.g., university, work, and sports) and does not know the music preferences of all her guests. Since Tina wants the party to be fun for everyone, she is highly interested in a solution that would gather the music and sharing preferences of her guests to create a blended playlist that would appeal to everyone at the party. However, she does not want to bias her personalized music algorithm, and would like to still be in control of the music that is played during the party. Hence, she decides to use *WeMix*, a decentralized system that allows users to share their music taste and create blended listening experiences while maintaining users' data privacy. Moreover, *WeMix* considers the four roles for controlling IoT devices in smart home environments proposed by Jang et al. [12], and which are present in Tina's scenario, namely:

- *Primary user*: refers to the main user of the device whose individual account is linked to (Tina).
- *Alternate primary users*: refers to somebody that might play the primary user's role, such as a significant other (Oliver).
- *Secondary user*: refers to someone that can use the device but with restricted permissions (Whitney).
- *Guest*: refers to visitors that are by default not authorized to use the device (the party guests).

3.1 Prototype Implementation

WeMix consists of three main components (see Figure 1): a) *Solid Pods* for decentralized storage of users' data and a server pod for storing *WeMix* session data, b) a *Server* running a web application for initial setup, the implementation of different music blending methods, and in charge of interacting with the Smart Speaker, and c) an *MR App* running on Microsoft HoloLens 2 (HL2) head-mounted displays. *WeMix* builds on the vision of pervasive, and everyday MR [4, 11], in which glasses are worn continuously and are therefore already available when a co-located listening situation arises. In this setting, an MR app lets each participant view preference information privately while the audio output remains shared, and lets them interact hands-free while attending to the social situation.

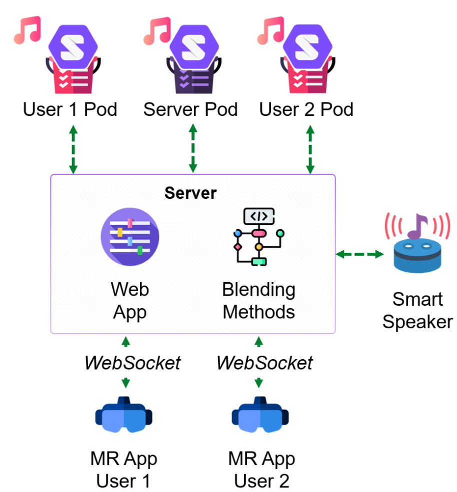

Figure 1: Overview of the *WeMix* components.

Solid Pods. Solid (Social Linked Data) is an initiative to empower users to be in control of their data[2]. Instead of users duplicating their data with different server providers and allowing them to process it as they wish, a user gets a single Solid Pod in which their data is stored. The user can then grant access and processing permissions to different applications at a granular level, remaining

[2]see https://solidproject.org

in control of their own data at all times, as they can change the permissions or stop access to their data at any time. In *WeMix*, a *User pod* hosts the user's music preferences (i.e. the user most listened to songs, top genres and top artists), as well as the user preferences on what music preference information to share with other roles (see Section 3). Finally, a *Server pod* stores current *WeMix* session information, including a list of active users.

Web App. A user new to *WeMix*, sets up their Solid Pod and populates it with their current music taste through a Web App hosted on the *Server*. After a new user gains access to their music streaming service account (i.e., Spotify), the app retrieves (upon user consent) the top 50 most listened to artists in the short term (around 4 weeks), the top 50 most listened to tracks in the mid term (around 6 months) and the user preferred music genres are obtained from the list of artists and tracks. We decided to implement this Web application as a one-time setup step, to avoid complicated mid-air gesture typing in the MR app.

Blending Methods. *WeMix* offers three methods that define how the music taste of two users are combined into a playback queue.

- The *Common method* aims to promote homophily [18], which is the tendency to seek fellowship or recognition from people that have the same music taste. This method is implemented by querying the top songs of two users from their Solid Pods, the artist and genres of those tracks are then obtained and compared between the two users. If a song is from an artist or is in a genre that the other user listens to, it gets added to a list. After completing this process for the top songs of both users, the list is shuffled and up to 50 tracks are added to the blended playback queue.
- The *50/50 method* provides an equal split, it combines the top 25 tracks of each user regardless of overlap, it shuffles these songs and adds them to the playback queue.
- Finally, the *Discover* method takes the opposite approach to *Common*, promoting heterophily [18], which refers to connecting with others by going outside of your personal music taste. Hence, *Discovery* takes the top songs of each user and selects those that are not common between them.

Server. The server is also in charge of communicating with the *MR App* (through WebSockets) the result of the blending methods, to notify the *MR App* when a new participant joins the multi-user playback experience, and to interact with the primary owner music streaming service to play music in the smart speaker.

MR App. When a new user enters the shared space and is detected by the system, the primary user receives a pop-up notification displaying the name of the new user and their role (e.g., alternate primary user or secondary user). The primary user then opens a screen showing the music preferences of the new user, a similarity score, and a menu that allows them to invite the new user to be part of the multi-user playback experience. As Figure 2 shows, the new user R likes alternative rock, german hip hop and progressive rock, while they dislike pop, noise, and ambient music. Similarity scores are computed via Jaccard similarity [14] ($J(A, B) = |A \cap B|/|A \cup B|$) over top artists and top songs, then averaged into a combined score. Each raw score $s \in [0, 1]$ undergoes a square-root boost ($100\sqrt{s}$) to correct for perceptual underestimation at low-to-mid ranges. If a user only shares top artists or top songs, only the mutually available data type is used to compute the score. On their side, the new user receives an invitation that shows the blending method that the primary user selected, their music likes and dislikes, as well as the similarity score between the two users. The new user can accept to be part of the experience or not.

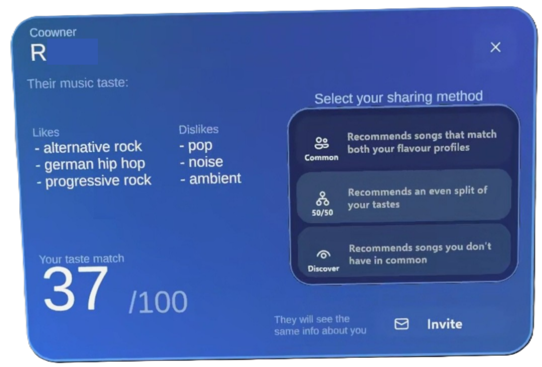

Figure 2: The view of the primary user in *WeMix* upon a new user arrival. It shows their name, role, liked and disliked genres and the match with the new user's taste. The primary user can then choose a blending method on the left and send an invite to the new user.

Once the new user has accepted, the session starts and both users see the track that is currently playing, as well as a queue preview. Each track in the queue is labeled with the name of the user from which it originated, giving both parties transparency over the shared listening experience (inspired by Spotify Blend). Users can also skip through the songs using this interface.

3.2 Prototype Validation

A preliminary user study was conducted with four male students (18–24 years of age). The participants were organized in two pairs to evaluate their comfort in sharing their music taste, and *WeMix*'s usability. Each pair completed four conditions, alternating between primary user and secondary user roles, under the following conditions: a) users decide to keep all their data private (top artists, top songs, and top genres). Hence, no similarity score or granular music preferences can be shown, b) only the similarity score is shown (even though the users share their data), c) only preferred genres are visible, and d) all data is visible. Here, the user can see the likes, dislikes and similarity score, as shown in Figure 2. After each condition, participants rated their comfort with the data shared, their understanding of the other user's music taste, and their satisfaction with the generated playlist. Usability was assessed using the System Usability Scale (SUS) [6], yielding a mean score of 75/100. Participants felt comfortable sharing data across all conditions and rated the generated playlists 3.94/5 on average. The Discover blending method was preferred the most, consistent with the findings of Park and Kaneshiro [18] on user preference for musically heterophilous playlists. Suggested improvements included the display

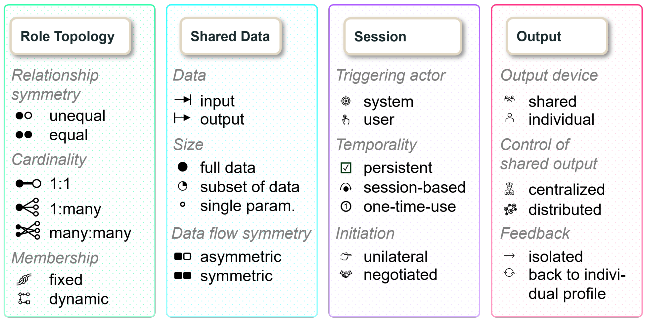

Figure 3: Preliminary design considerations for shared multi-user personalized experiences in smart environments

of additional contextual information prior to decision-making and enhanced playback controls. These results should be interpreted as preliminary given the small and homogeneous sample size. A larger study with a more diverse set of users and environments would be needed to comprehensively evaluate *WeMix*.

4 Design Considerations for Shared Multi-User Personalized Experiences in Smart Environments

During the design and implementation of *WeMix*, we repeatedly faced decisions that, we believe, recur in many shared multi-user personalized experience in a smart environment. In this section, we sketch these decisions as preliminary design considerations along four categories (see Figure 3). They sit at the intersection of work on multi-user smart home use, Group Recommender Systems (GRS), and recent work on sharing and privacy techniques in multi-user XR, and build on our earlier work for sharing such content [27, 28]. The intent is not to present a complete or validated framework, but to identify potential dimensions that a designer of such systems could address and to position *WeMix* as one implementation within the resulting space.

Role Topology captures who is involved and how a group is structured. We identify three sub-dimensions: *relationship symmetry* (whether participants have equal or unequal standing and permissions), *cardinality* (1:1, 1:many, or many:many), and *membership stability* (whether the set of participants is fixed over the lifetime of the sharing or changes during it). The first sub-dimension draws on Jang et al.'s multi-user IoT roles [12], and on the broader work on tensions and power asymmetries among cohabitants of shared smart devices [10, 25]. The latter two reflect observations from GRS research that composition and stability shape how a useful group recommendation looks [2]. *WeMix* is unequal in standing, since the four-role model from Jang et al. [12] grants different permissions to the different roles. It supports cardinalities from 1:1 (Tina and Oliver at home) to many:many (at the party), and its membership is typically dynamic, as guests arrive and leave during a session.

Shared Data describes the data exchanged among the participants. We suggest three sub-dimensions: the *data*, *size*, and *data flow symmetry*. The *data* distinguishes whether *input data* that feeds a personalization algorithm or *personalized output* rendered to users is shared among them (cf.[28]). The *size* of the shared data can be a full personal profile, a subset of it, or even a single parameter, connecting to relevant work on fine-grained data sharing controls in everyday MR [1, 21]. *Data flow symmetry* captures to which extent participants contribute with their data. *WeMix* shares input data, a subset of the users preferences (top artists, top tracks, and top genres), and follows a symmetric flow in which users contribute and benefit from the shared data.

Session captures the way a sharing session starts and its length. We identify three sub-dimensions: the *triggering actor* (user or system), *initiation* (unilateral, or negotiated with other parties), and *temporality* (whether the sharing is persistent, session-based, or one-time). The negotiated case is closely related to recent work on dynamic, multi-user privacy negotiations in shared MR [20]. In *WeMix*, both system and user are involved: the HL2 senses a new co-located user, but the primary user must explicitly invite them before any sharing begins, so the act of initiation rests with the user. Initiation is also negotiated, as the invitee can accept or decline, and temporality is session-based, lasting only as long as the listening session.

Output describes how the personalized result is delivered and the consequences it brings after the sharing experience ends. We sketch three sub-dimensions: the *output device* (shared, such as a smart speaker, or individual, such as a personal headset), *control over a shared output* (centralized in one actor or distributed across multiple or all the participants), and *feedback* (whether the shared session's content feeds back into each participant's individual profile or not). The first sub-dimension relates to works on smart speakers (cf. [16, 25]), that document how a shared communal output device reshapes interactions and expectations among cohabitants. In *WeMix*, the audio output is shared via the smart speaker while queue overview is delivered individually on each participant's HL2. Control over the shared queue is distributed, as each user can skip from their own headset. Feedback is currently coupled, since playing the blended queue through Spotify implicitly trains each contributor's recommender, which is exactly the concern Tina raises in our scenario.

5 Conclusion

WeMix is a decentralized prototype that explores how co-located users can blend their individual music preferences into a collective listening experience while remaining in control of their data. *WeMix* provides transparency in the blending process by allowing users to see each other's music likes and dislikes before selecting a blending method via an MR app. Through the development of *WeMix*, we identified four preliminary design considerations to consider when designing shared multi-user personalized experiences in smart environments: *Role Topology*, *Shared Data*, *Session*, and *Output*. In future work, we aim to evaluate these dimensions with more co-located and diverse user groups using *WeMix*, and work towards a validated framework to guide designers in creating shared multi-user personalized experiences in smart environments.

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