Spotify Warped: Reshaping Personal Informatics via Music Listening, Casual Users, Passive Data and Episodic Reflection

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Abstract

Analysing personal datasets has traditionally been limited to 'Quantified Selfers' who commit significant effort into manually recording and analysing their data. However, the pool of Casual Users (CUs) who *can* engage with their personal data is increasing due to the prevalence of companies passively collecting user interaction data. In this paper, we execute an online survey exploring what kinds of information users seek about their music listening behaviour. We compare the information needs of CUs to identified Self-Trackers, using music listening as a lens to develop an information space. The paper culminates in a provocation to broaden the audience of personal informatics by updating existing models of interaction to account for casual users, passive data, and episodic reflection.

CCS Concepts

• **Human-centered computing → Empirical studies in HCI**.

Keywords

music listening, personal informatics, survey

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1 Introduction

Research in personal informatics (PI) has traditionally focused on users who are Quantified Selfers (QS), typically placing an emphasis on domains driven by goal-oriented progress such as health and fitness [22] (§2). QS users are defined as those who put considerable effort into **manually** recording, collecting, and analysing data about themselves[37]. Existing frameworks explore the various challenges these users face when interacting with their personal datasets[9, 23, 35].

Increasingly, personal data is being **passively** collected by companies as a by-product of a user engaging with a service such as music or video streaming, fitness trackers, and even device screen-time usage. The introduction of data privacy laws such as General Data Protection Regulation (GDPR) mean that any user who has data collected about themselves can request access to it, meaning the pool of users who can access, and learn from, their data is growing.

As a result of this, the manual burden of tracking typically associated with the QS movement is reduced, introducing a new class of **Casual Users (CUs)**[1] who should now have access to their personal datasets.

The emphasis in prior research on dedicated QS users leaves a gap in understanding how CUs engage with their data. For instance, systems that passively collect data now offer **episodic overviews** – provider-curated infographics and summaries – that surface some of this data back to a user at regular, often annual, intervals. This is a primary mode of interaction with personal data for CUs; however, compared to QS, we know little about the kinds of insights that CUs *want*, what data they value, and how well these existing summaries serve them.

Understanding CUs' interactions with personal data is valuable for Personal Informatics to understand how users with varying levels of data-literacy and willingness to engage end up interacting with their data. It can drive research into how personal data can directly impact users even when they do not actively track, and into what methods are most effective for surfacing insights. Moreover, the passively collected datasets that CUs rely on also exist for QS users and exploring users' interactions with these datasets and the provider-curated summaries can facilitate more effective design of episodic summaries as well as the potential expansion of QS practices.

Music listening presents a compelling domain to explore this gap of understanding into CUs' data interactions and preferences. Streaming platforms collect **fine-grained behavioural data** over long periods with no manual effort required from users. Additionally, the annual summary provided by Spotify[2] – Spotify Wrapped – is widely regarded as one of the most successful and popular examples of episodic overviews since its introduction in 2015[15, 16], repeatedly generating large-scale user participation and viral social media activity[41]. The clear popularity of Spotify Wrapped to a broad range of users (Fig. 1) means music listening represents an ideal lens to explore casual users, passive data, and episodic interaction.

The success of Spotify Wrapped has spurred yearly overviews not only from other music providers (Apple Music, Tidal, YouTube Music) but also in myriad domains including language learning

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[1] See §1.2 for operational definitions
[2] The market leader in music streaming

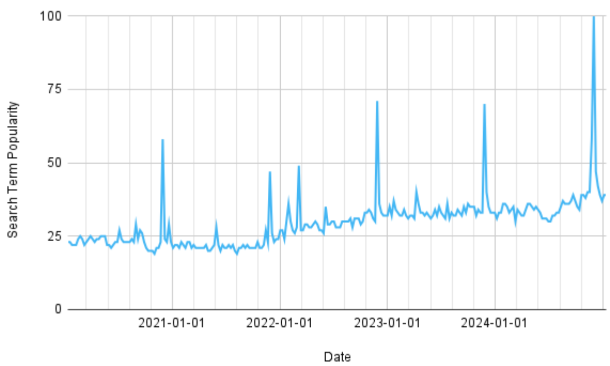


Figure 1: How the popularity of Spotify as a search term has changed over the past 5 years on Google. There is a significant peak every year coinciding with the release of Spotify Wrapped in late November, early December.

(Duolingo), news sites (Washington Post, Newsprint), fitness tracking (Strava), social media (Reddit), and many more[16, 41]. However, these summaries are typically limited to simple shareable static graphics (§6). As a result, CUs engage only **episodically** with their personal data – when companies surface insights for them – rather than through **continuous self-directed tracking**.

Thus, while these campaigns broaden the audience of data engagement beyond QS users, the rigid templates do not facilitate exploration and limit the capabilities of users to meaningfully engage with their behaviour.

1.1 Contributions

In this paper we conducted an online survey with 60 participants. Through the analysis of this survey, we make both **domain-specific** and **broader theoretical** contributions – offering empirical insights into how people engage with music listening data as well as broader implications for the personal informatics literature:

Domain-Specific Contributions.

- Empirical reporting of users' specific data interests related to music listening behaviour (§4.2) and analysis of the abstract insights they sought (§5)
- A description of the current landscape including an evaluation of existing music listening summaries (§6) and barriers that users face (§6.4)

These domain-specific contributions illustrate the potential for music listening as a setting for users to engage with personal informatics that falls outside of traditionally studied domains - §2. We hope that they can also motivate development of consumer-facing overviews that better serve users and facilitate interaction with personal data that more closely matches their desires.

Broader Theoretical Contributions.

- We propose an **information space** framework for describing the types of insights users seek from passively collected personal data, informed by music but generalisable across domains – §5
- We outline a conceptual provocation that highlights limitations in existing models of personal informatics when applied to Casual Users, episodic overviews, and passive data contexts – §7

Through these *broader implications* we provide mechanisms for further research to better characterise the kinds of interactions users can have with their personal data and to illustrate how passive data and episodic reflections are changing the landscape of personal informatics. Our provocation aims to advance future research by identifying how these emerging user types and modalities require the augmentation of existing models of personal informatics[9, 21, 35, 46] and how this can broaden the audience beyond traditionally studied domains and users[4].

1.2 Definitions and Terminology

To support clarity in our comparisons and contributions, we define key terms used throughout the paper.

A spectrum of data engagement. - Throughout this paper we refer to three user groups: **Quantified Selfers**, **Self-Trackers**, and **Casual Users**. These groups exist along a spectrum of data engagement and the boundaries between the groups are sometimes fluid. We define each based on their levels of intentionality, effort, and domain breadth below, and summarise in Table1.

Quantified Selfers invest significant time and effort into recording, analysing, and reflecting on data about themselves[37]. This engagement is characterised by **active**, **conscious** decisions to track their behaviour often across multiple domains using manual and automated approaches. They engage deeply with **all stages** of the stage-based and lived informatics models of personal informatics[35, 46], and this engagement is often a **continuous**, **iterative** process. QS users have been the focus of much **prior research**, particularly work trying to understand these users' approaches to and goals of data engagement[9]. When we refer to QS users in this work we are referencing these users that have been studied in **prior work**.

Casual Users refers to individuals **in our study** who fall at the other end of the data engagement spectrum. They exclusively **passively** create data through their interactions with services like music streaming platforms but do **not** consciously track or engage with this data. Their engagement is typically **episodic** and driven by provider-generated insights. CUs bypass most stages of the informatics life cycle, often only engaging in prompted *reflection*.

Self-Trackers occupy a middle-ground between CU and QS users. They exhibit **conscious** engagement with some form of personal data tracking and demonstrate some **awareness** and **engagement** with their data domains, but lack the broader, more in-depth, engagement of QS users. Oftentimes engagement is confined to a single domain and significantly less involved – for example, occasionally keeping track of books read, but not religiously updating the list. As a result ST users do engage with some stages of the personal informatics data lifecycles but less thoroughly and more sporadically than their QS counterparts. Self-Trackers is a term that has appeared in previous literature but in this work we use it to

Table 1: How different user groups exist along the spectrum of data engagement and interaction with the data lifecycle

	Quantified Selfers (QS)	Self-Trackers (ST)	Casual Users (CU)
Data Engagement	High	Moderate	Low
Data Lifecycle Stages	Full Engagement	May skip some stages (e.g. Preparation)	Passive Reflection Only
Agency	High (conscious, engaged tracking)	Medium (May rely on apps)	Low (data passively collected only)
Motivation	Behavioural Change, Curiosity	Habit Tracking, Curiosity	Curiosity, Reflection
Specifically Investigated in this Study?	No	Yes	Yes

refer to a specific subset of the users from **our study**. We detail our criteria for this in §3.4.

Passive Data refers to information collected as a by-product of user activity, rather than through deliberate tracking. In this paper, music listening logs gathered automatically by streaming platforms exemplify passive data.

Episodic Overviews are curated summaries or infographics periodically generated by service providers (e.g. Spotify Wrapped). Unlike continuous self-tracking, these overviews offer time-bounded, provider-selected glimpses into users' behaviour.

2 Related Work

2.1 Personal Informatics

Personal informatics (PI) research has traditionally focused on Quantified Self (QS) and Self-Tracking (ST) users' interactions with their personal data. To describe this relationship, Li et al. established the Stage-Based Model[35] – a five stage lifecycle that spans from *preparing* and *collecting* data through to *reflecting* and *acting* (Figurre 2a). This model was updated and expanded to better reflect real-world self-tracking behaviour in Epstein et al.'s Lived Informatics Model[23, 46] which considered stages such as *deciding*, *lapsing*, and *resuming* tracking. This updated model also emphasised the cyclical nature of tracking in the real world (Figurre 2b) as well as the flexibility, range of different tracking domains, and emotional factors in self-tracking. However, it still largely assumed intentional, active engagement with data. Although both of these models have been tweaked for specific populations[54] they continue to represent the primary means of describing users' interactions with personal informatics (PI).

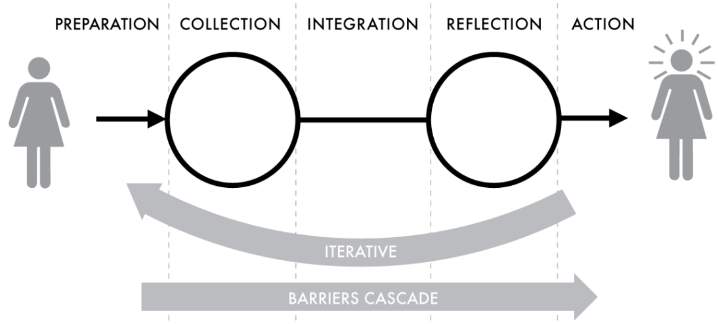
Work building on these models has also focused on later stages of the lifecycle – especially on what users want to learn from their personal data. The disconnect between data collection and insight generation has been highlighted[21, 22] and formalised as the "Personal Informatics Analysis Gap" – the difficulty users face in extracting meaningful insights from their data [40]. One such gap is discussed by Rapp and Cena, who explored how **casual users** with no self-tracking experience engaged with personal data[44]. However, this work focused on these users *becoming* users who actively collected, tracked, and analysed their data and not on their *existing* data, their data relationships, or how the friction of their engagement could be lessened. Their findings showed decreased motivation in *actively* tracking their data, mirroring findings from work examining abandonment of tracking[1, 10].

On the other hand, work focusing on insights that users extract has again focused on QS users, considering the kinds of visualisations used to present insights at QS meetups[7] and more broadly the field of personal visual analytics[30]. Existing PI literature has also established concrete reasons *why* QS users track their data, such as behaviour change, self-reflection, and reminiscence[35, 46] and more formally described five different categories (*Directive*, *Documentary*, *Diagnostic*, *Reward*, and *Fetishised*), also focusing on how users' data engagement was an **emotional** task and not purely analytical[23, 46]. The primary focus of a significant portion of PI work has been in behavioural change and often focused in the domain of health and fitness[22, 25]. While some work has suggested the focus on behavioural change is disproportionate[52], only limited work focuses specifically on other tasks such as self-reflection or reminiscence[51].

Prior work that has focused explicitly on reflection has explored different temporalities that emerge for users [26] as well as a diverse set of tasks that users engage with when self-reflecting, often emphasising the exploration that users undertake[8]. More broadly, Lupton's typology of self-tracking also considered reflective practices across social and cultural contexts[36]. Outside of PI, research has also focused on how active recording of data can trigger self-reflection in work contexts[29]. All of this work primarily pairs reflection with active data collection and deliberate self-tracking practices. In contrast, we examine reflection and interaction when data is collected passively and only surfaced to users through provider-triggered overviews.

Amongst the PI literature, the concepts that we focus on in this paper of **casual users**, **passive data**, and **episodic** insight are not unique to the domain of music listening. Alluding to **casual users**, the lived informatics model[23] identified differing levels of commitment to self-tracking, which has been illustrated in domains such as fitness tracking[58]. However, as detailed above, prior research has largely addressed casual users by focusing on how to make self-tracking easier[44] rather than investigating casual users' existing personal data interactions. Related to **passive data**, work has considered the use of technology to more easily collect data[6], though this work still relies on active user initiation of this tracking and users' invested and involved engagement with the collected data. Finally, research has considered STs **episodic engagement** with PI[27], however often focused around specific care tasks and goal-oriented outcomes of interaction. This differs from the more curiosity-driven interaction we discuss in §4.2 and §5. In addition, prior work also details how the periodicity of interaction is still driven by the user themselves[36] instead of the episodic overviews that we focus on that are triggered by providers.

This paper builds on existing literature to understand how well existing QS frameworks can describe more **casual users'** information needs, their relationships with their data, the emergence of **passively** created data sources, and the proliferation of **episodic overviews**. Moreover, domains such as fitness and health have



(a) Figure taken from Li et al.'s Stage-Based Model [35]

(b) Figure taken from Epstein et al.'s Lived Informatics Model [23]

Figure 2: The two most prominent models of personal informatics engagement.

seen extensive focus in existing work especially considering behaviour change and goal-oriented interactions as a key driver[22]. By focusing on the relatively unexplored domain of music listening we hope to reduce this focus on behavioural change and gain further understanding of the information needs of users engaging with their data.

2.2 Music Listening

Prior work in the music listening domain has analysed large datasets [24, 43] and social media posts[57] to establish formal models of music listening behaviour. Relatively little work takes a user-centric approach. A notable exception is Kamalzadeh et al.'s 2012 survey (> 200 users) which examined users' listening habits[31]. This work focused on music library management but also laid out how users self-reported consuming. We extend some of these findings in §4.1 and contribute to work that has investigated how users' listening has changed in the advent of digital streaming[14].

Other studies have evaluated how well users' self-reported listening behaviour aligns with their measured behaviour[18]. Research in the psychology domain has attempted to understand some of the drivers behind music listening behaviour and preference[47] without touching on the specific attributes of music that users are consuming.

Prior work on retrieval and discovery of music has often involved inferring behaviour from datasets of music listening[24]. This work has focused on how this information can be leveraged to improve music recommendations for listeners, facilitate easier discovery and retrieval of music[33], or to drive better interactions with music listening apps[56].

The common theme of this prior work is in understanding the **listening behaviour** of users. In contrast, our work focuses on what users can, and want to, learn from their listening behaviour, engaging with their self-reported preferences.

Finally, as we outlined above (§2.1) the focus of work in the PI domain has historically been on health and fitness with Epstein et al.'s 2020 personal informatics literature review establishing that 83% of publications touched on some aspect of health[22]. In contrast, music listening is a relatively untapped domain area for PI and does not feature as one of the 20 named domains identified from the 523 publications surveyed. This domain has potential to provide nuanced insights into the personal informatics space.

Limited PI work has explored music listening, leveraging visualisation in tandem with users' music libraries or histories to facilitate easier navigation of music[53], and considered the use of users' music listening history in the context of social interviews[13]. However, to our knowledge, no existing work has focused on establishing what users would like to learn about their *own* behaviour from their listening histories, and which specific aspects are of most interest to them.

3 Methodology

We conducted a crowdsourced study with 60 participants from the Prolific platform.

3.1 Survey Design

Our survey was split into 5 sections.

A - *What do users want to learn from their music listening history?* At the beginning of the survey we asked users to provide a minimum of 3 insights they would like to learn about their music listening as a set of open-text responses. There was a further (optional) opportunity for respondents to suggest insights at the end of the survey – though few (7 out of 60) participants did.

B - *Users' relationship with music.* To compare users' listening behaviours to previous work (§2) and investigate how individual differences potentially impacted other responses, we asked several categorical multiple-choice questions, often allowing multiple responses to one question and further open-text responses. These questions covered topics such as how often users listened, what medium they used, and in what contexts they listened.

C *- What attributes of music are users interested in?* In addition to understanding the *abstract insight interests* of users in **A**, we sought to characterise users' specific *data interests* related to music. The questions focused on 4 areas: Artists, Albums, Tracks, and Listening Sessions (continuous sessions of listening with no significant pause between songs). Additionally, three sub-areas (Lyrics, Musical Features, Musical Credits) were asked conditionally based on their indication of interest to questions related to the initial key areas.

Each of the area questions consisted of 5-point Likert questions (1 = 'Not at all interested', 3 = 'Neutral', 5 = 'Very interested') eliciting the user's interest in certain aspects of the area (e.g. Artist Age, or Track Release Date). In addition, every question allowed the user to offer free-text responses for additional criteria we may not have considered.

D *- Barriers to accessing more insights into their behaviour?* A mix of multiple-choice and free-text answers designed to understand whether users wanted access to their full listening history, and what barriers existed.

E *- Attitudes towards existing summaries.* Finally, we surveyed users' current attitudes towards the summaries that music streaming providers offered. In combination with **C** and an investigation of the existing summaries' capabilities (§6.1) this served to establish how well users' desires were being satisfied. This section was split into Likert responses regarding the content of existing summaries from popular providers extracted in §6.1 (Total Listening Time, Top Genres, Top Songs, Top Artists, Top Albums, Top Playlists). We allowed open-text for each of these sections.

The full survey materials are included in supplemental material.

3.2 Data Analysis

3.2.1 Quantitative. Throughout our survey we collected a wealth of Likert scale and multiple choice responses. We analysed these by providing summary statistics and calculating means. As can be seen in Fig. 6, we additionally report raw response counts to show the distribution [48]. In §4.2 we also carried out independent t-tests to test for statistically significant differences in responses between Self-Tracking users (§3.4) and CUs.

3.2.2 Qualitative. The vast majority of responses that required qualitative analysis came through the free-text insights users provided in section **A** of the survey. In total we received 215 insights – 202 at the start of the survey, 13 during the (optional) final question.

We first applied an inductive open coding approach[12] beginning with the data to establish low-level codes. Two authors initially coded random subsets of 5 insights, discussed and calibrated, and repeated this approach until agreement was reached. Drawing inspiration from previous work[19], we iterated over the full response set, establishing a set of 29 stable codes after 3 full independent passes.

We created additional structure of our codes using thematic analysis[5] via an affinity diagramming approach[28], utilising the online whiteboard software Miro[39]. This process was, again, an iterative discussion between the authors.

Throughout the survey we also received free-text responses on multiple other questions and applied a similar qualitative analysis

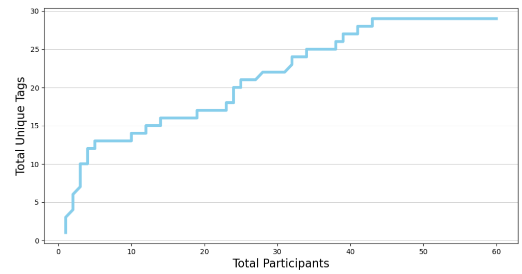


Figure 3: Total number of unique insight tags vs total number of participants

methodology. The full responses and processed results of *all* survey questions are included in the supplemental material.

3.3 Survey Recruitment

Participants. We recruited 60 participants (28 men, 30 women, 2 nonbinary) located within the US from the crowdsourcing platform Prolific. To be eligible for the survey, participants needed to indicate they used a music streaming platform in Prolific's pre-screening questions. The age of participants ranged from 18-64 (μ = 35.33, σ = 11.77). 42 participants indicated they were White, 7 Asian, 6 Black, 2 American Indian or Alaska Native and 7 listed 'Other'. The majority of participants indicated their highest level of education involved higher education: 22 with a bachelor's degree, 5 master's and 5 doctoral. 19 indicated they had completed high school.

While Prolific is widely used for HCI research and offers access to diverse demographics, our sample is nonetheless limited in representing purely US-based participants with reliable internet access and potentially higher levels of technology literacy than the global population. Our results thus represent an initial exploration of this domain and may not generalise to other populations.

Participants spent on average 20 minutes on the survey and were compensated $5. All participants answered the survey in October/November 2023, *before* that years' yearly overviews were released. In §4.1 we detail how 7 users responded that music had 'no specific role' in their life to an early survey question; as the purpose of this work was to understand what users want to gain from insights into their music listening behaviour, we excluded these results from the quantitative analysis in the rest of the survey.

Stopping Criteria. Previous literature examining people's listening preferences[31, 34] has worked with sample sizes in the hundreds. However, in order to allow us to explore greater qualitative depth in the answers to our questions, we worked with a smaller sample. To ensure we still reached saturation in our analyses we recruited in increments of 10 and performed analysis of the answers incrementally. For the quantitative analysis of responses to the Likert style questions, we visually inspected the change in mean response of users as we increased the number of participants (e.g. Fig. 4).

Similarly, for the qualitative analysis, after each new set of 10 participants we executed a round of open-coding with two authors assigning inductive codes and comparing them. We then inspected how the total number of unique tags varied. When we recorded a

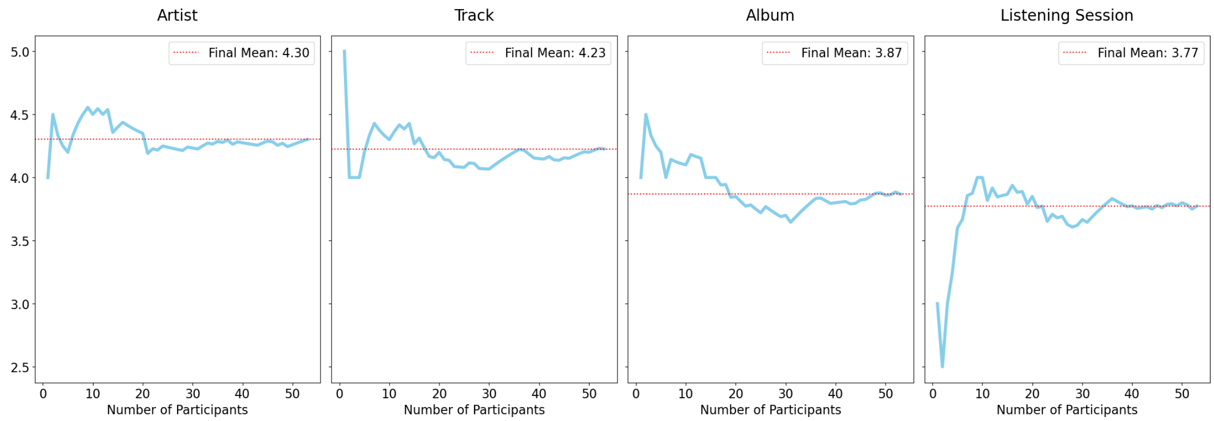


Figure 4: Mean response to users' general interest in areas of music as the number of participants is increased

full set of 10 participants but added no new tags we determined we had reached saturation. This can be seen in Fig. 3. Once we had reached saturation of these tags for the user-recorded insights we then performed the more formal coding approach detailed in §3.1.

3.4 Self-Tracking Behaviour

As discussed in §1.2 we operationally defined Self-Trackers as a type of user falling between QS and CU users on the data-engagement spectrum. A focus of this paper was to investigate how information needs and desires may differ between users with differing levels of data-engagement – namely between CUs and STs.

In order to identify ST users, we asked two questions at the end of section **B** of the survey:

(1) "Do you manually record data about your music listening habits?"
(2) "Do you manually record data about other aspects of your life? (e.g. books read, financial tracking)"

Using open coding (full codebooks and analysis available in supplemental material) we categorised the open-text responses to these questions in a 5-point scale of tracking behaviour:

(1) User does not display any tracking behaviour
(2) User shows minimal potential behaviour indicating possible awareness of their behaviour but not tracking it
(3) Occasional or idle tracking behaviour
(4) Substantial tracking behaviour
(5) Extensive tracking behaviour (e.g. recording extensive information about specific behaviour or maintaining multiple lists of habits)

We ultimately determined the threshold for classification as a **Self-Tracking** user to be users who were coded as a 4 or higher on this scale. We chose to exclude those with a rating of 3 as these responses were often ambiguous in describing the extent to which they *manually* engaged with the tracking process as well as their overall involvement with and awareness of the data once it was collected, e.g.: P12 - "I use an app to record the books that I read". In contrast, those coded as 4 or above clearly indicated their continued engagement with their data, e.g.: P6 - "I keep track of my progress with weight lifting in my phone's note app."

Although those coded as 3 potentially reach the threshold of Self-Trackers we chose to err on a conservative definition to try to ensure a group who were invested in their data.

Very few participants exhibited any form of self-tracking behaviour in the music domain. As shown in Fig. 5, only 8 participants (13%) displayed substantial or extensive tracking behaviour related to music. This aligns with prior research that has examined the range of domains that users track data in. Music listening does not appear in the top 20 domains surfaced in Epstein et al.'s 2020 survey [22], and their interactive tool only highlights 1 out of 584 articles as focusing on music listening[3].

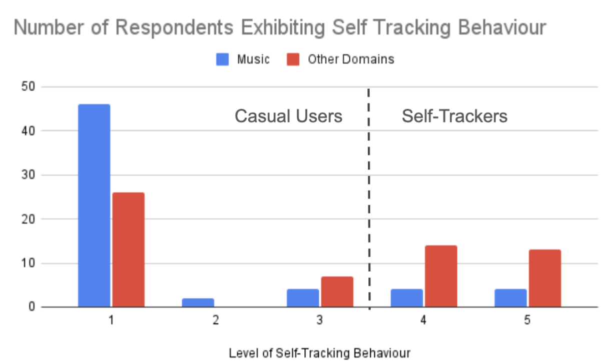


Figure 5: Prevalence of self-tracking behaviour in our respondents across music and 'other' domains.

Due to the scarcity of self-tracking behaviour in the music domain, relying solely on these users would have created a group that was too small and heterogenous to facilitate meaningful comparison. As a result we made a pragmatic decision to operationally define **Self-Tracking (ST)** users as those who scored 4 or above with regards to tracking data in 'other' domains, totalling 26 users. The remaining 27 users (those who did not reach the criteria for ST) are referred to as **Casual Users (CUs)** in this paper. We utilise

[3]http://personal-informatics.depstein.net/

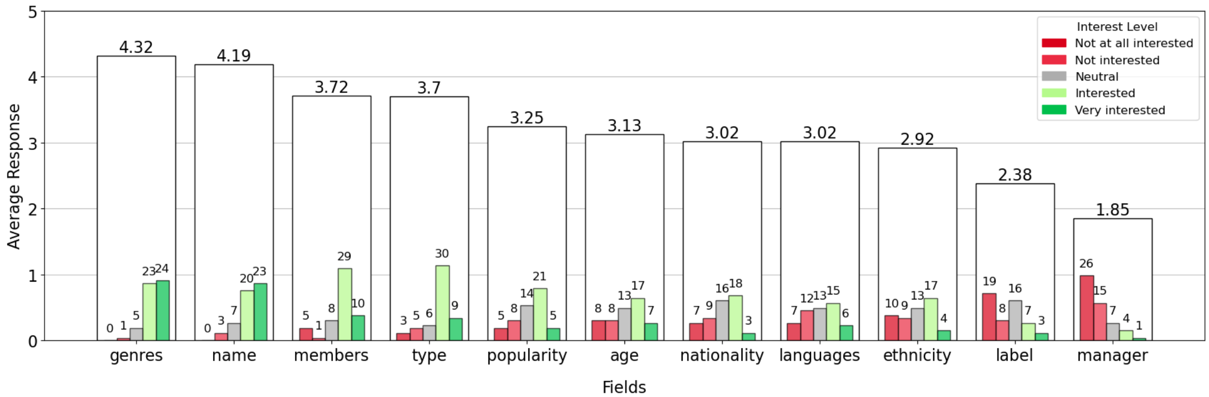


Figure 6: Interest in different aspects of information relating to Artists. Large bars represent mean responses and small bars the distribution of responses.

this definition for clarity and to occasionally distinguish them from QS users studied in previous work.

This threshold is inherently pragmatic rather than definitive. However, in this work we are not aiming to define a stable typology but to perform initial exploratory work to investigate whether prior experience with self-tracking – regardless of domain – corresponds to different patterns of data interests.

It is also likely that some of our ST users reach the threshold of QS but we did not fully investigate this through our survey and so instead describe these as separate groups in the remainder of this paper.

In using this definition we were able to facilitate more meaningfully sized groups for comparison (compared to relying only on music self-trackers) and to explore whether users exhibiting self-tracking behaviour *regardless of domain* influenced their relationship with data (§4.3) and the abstract insights they sought (§5.4).

4 Quantitative Findings

4.1 Music Listening Behaviour

In **Section A** of the survey (§3.1), we sought to understand users' listening habits to contextualise users' attitudes toward music data. Responses were generally consistent with prior research[31], with participants reporting a **wide range of listening contexts**, most commonly as accompaniment to other activities (e.g., working, commuting, exercising). Nearly all listened to music **daily**, typically in sessions of **30 minutes or more**.

A key shift from earlier studies was the dominance of streaming: over 85% used streaming as their primary method, compared to Kamalzadeh et al.'s 2012 study where 61% reported they did **not** use online music services. **Spotify was the dominant provider** (80% of respondents), whilst Pandora was commonly used by a slightly older demographic. We explored whether differences in users' listening behaviour influenced their survey responses in other sections but found no clear patterns. Full results are included in supplementary material.

4.2 Users' Music Data Interests

Based on responses to survey section **C** (§3.1), we report users' *data interests* in 4 key areas of music consumption, each of which is broken down into several constituent features: **Artist** (age, nationality...), **Track** (duration, release date...), **Album** (genre, number of tracks...), and **Listening Session** (duration, number of artists...). The first 3 areas encompass information directly related to the music, whilst listening sessions cover how a user consumes this music. Unlike prior work(§2) these findings are **not** reporting the consumption behaviour of users but instead focus on the preferences recorded by users into data that is most interesting to them in the context of **learning more about their listening history**. We present the pertinent **Takeaways** below, labelled **T1 - T9** for later reference.

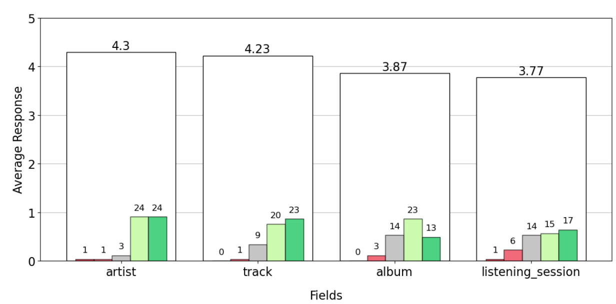


Figure 7: General interest in areas of music consumption.

These takeaways can offer a starting point for future research to explore *why* these data points are of most interest to users and whether they align with the abstract insights that users seek from their data (§5). Furthermore, they can also be used to inform the design of tools (both episodic and exploratory) for presenting insights into users' listening behaviour to users.

***T1** - Users are most interested in information pertaining to Artists and Tracks.* Conversely, users expressed less interest in albums and listening sessions (Fig. 7). This may be indicative of how streaming as users' primary form of consumption has led to less focus on album listening – the primary form of consumption in CD or vinyl form – and more focus on curated, personalised playlists[3, 14].

T2 *- People Love Genre.* Across all areas we see genre routinely rated positively. It was the most popular attribute in **all** of the core areas: Artist (μ = 4.32), Track (μ = 4.49), Album (μ = 4.43), and Listening Sessions (μ = 4.19), echoing the findings of the Kamalzadeh survey[31].

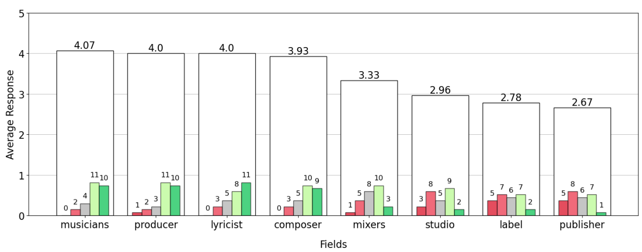


Figure 8: Interest in different aspects of Musical Credits.

T3 *- People are more interested in creators than distributors.* 27 participants indicated interest in **Musical Credits** associated with a **Track** or **Album** and were subsequently asked which credits they were most interested in. Fig. 8 shows an increased interest in those directly involved in the creation or recording of music (musicians, producer, lyricists, composers) whilst those responsible for distribution or management (mixers, studio, record label, publishers) scored much lower.

T4 *- People like general, summary information.* Approximately half of participants indicated they had more than neutral interest in either **Musical Features** or **Credits**. In contrast, we saw very positive reactions to general information, such as listening session duration (μ = 4.04), number of tracks (μ = 4.02) or artists (μ = 4.00). We saw a decreased level of interest surrounding specific data relating to listening such as the time of day they were listening (μ = 3.17) or the day of the week (μ = 2.98).

T5 *- People care how fast a song is, not whether it's sad or not.* 28 respondents indicated their interest in **Musical Features** related to a **Track** and were asked which features they found most interesting. Tempo (μ = 4.43) was the only feature that received significant amounts of positive interest, with one user indicating neutral, and the rest interested or very interested (next highest average: musical key μ = 3.96). Features relating to emotional sentiment of music (valence (μ = 3.68) and mode [4] (μ = 3.64)) were of much lower interest.

T6 *- People are interested in words (kind of).* Compared to the other conditional questions (**Musical Features**, **Musical Credits**), interest in **Lyrics** was significantly higher, with 40 participants indicating they were at least 'interested' (μ = 4.0). However, interest in specific information relating to **Lyrics** was lower ranging from μ = 3.18 (lyric repetitiveness) to μ = 3.78 (lyric sentiment).

T7 *- Context is polarising.* Some of the responses relating to specific listening context (e.g.: the weather when they listened) attracted the most polarising responses, with few users neutral, and peaks of interested and not interested. Some of this disparity is

[4]Whether the track is in a major or minor key.

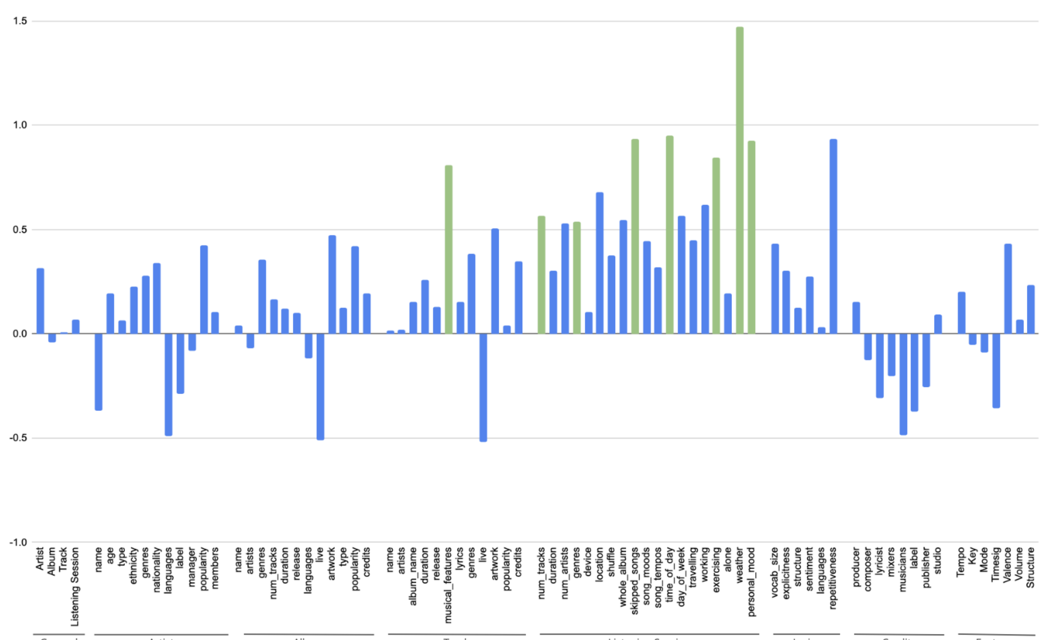


Figure 9: Average difference in rating between ST and CU users for each of 79 features. Green bars indicate statistical significance

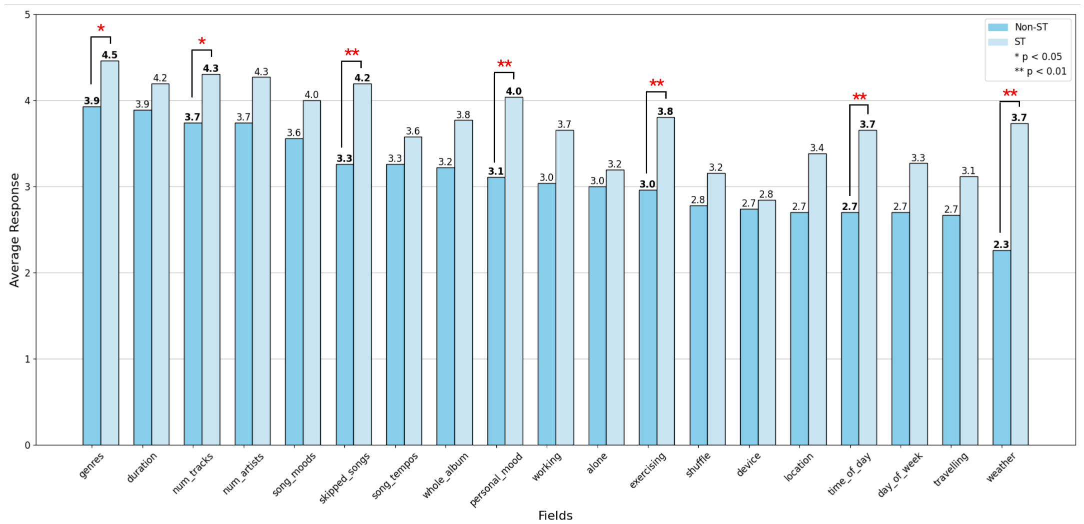


Figure 10: Comparison of mean interest in attributes related to Listening Sessions for STs and CUs

explained by ST user differences (**T9**) but can be contextualised by considering the wide range of contexts reported in §4.1 where not every context is relatable to every respondent.

4.3 ST Differences

We compared and contrasted how the data interests of ST users – defined in §3.4 – differed from CUs. To do this, we compared the mean responses of ST respondents to CUs. Although this work is still exploratory in nature, we performed independent t-tests to check for statistical significance across all 79 of the different features we investigated. Full results are included in supplemental material; here we report some high-level takeaways. Where the difference was found to be statistically significant, we make this clear in the writing.

***T8** - Self-Trackers are generally and specifically more interested.* Across all 79 features we saw elevated mean responses in 61 (Fig. 9) for ST users compared to CUs with 9 of these being statistically significant.

We found that STs had markedly increased levels of interest in many of the more *specific* aspects. In the case of **musical features** this increase was **significant** (μ_{CU} = 3.00, μ_{ST} = 3.81, t(51) = 2.29, **p < 0.05**) and marginal for **musical credits** (μ_{CU} = 3.04, μ_{ST} = 3.38, t(51) = 1.00, p = 0.3) indicating that ST users might be more interested in learning about specifics. In addition, we saw a **significant** jump in interest in the **repetitiveness of lyrics** (μ_{CU} = 2.68, μ_{ST} = 3.62, t(38) = 2.84, **p < 0.01**) as well as marginal for the size of vocabulary (μ_{CU} = 2.95, μ_{ST} = 3.38, t(38) = 1.07, p = 0.29) showing an inclination for ST users to analyse behaviour through quantification and understanding patterns.

We speculate that the reason for this increase in interest may be due to a generally increased investment in data. Our ST users all indicated tracking behaviour in some domain and therefore are likely to have interacted with data in these domains. This could indicate an inclination to consider data features that other users may not have. In addition, involved interaction with data in their other self-tracking behaviours could also suggest higher data literacy in general.

***T9** - ST Users are much more interested in Listening Sessions and Context.* The most striking takeaway from our analysis of ST users was that of the 9 features that showed a statistically significant increase in interest, 7 of these fell within the Listening Sessions area where *every field* showed an elevated interest for STs and the difference being **statistically significant** for the number of tracks($t(51)$ = 2.37, **p < 0.05**), genres($t(51)$ = 2.31, **p < 0.05**), skipped songs($t(51)$ = 3.69, **p < 0.001**), time of day of listening($t(51)$ = 2.80, **p < 0.01**), whether the user was exercising ($t(51)$ = 2.77,**p < 0.01**), what the weather was($t(51)$ = 4.38, **p < 0.001**) and the user's personal mood($t(51)$ = 3.23, **p < 0.01**).

In particular, the large jump in interest in context-specific attributes (weather, personal mood, exercising) also reflects ST and QS users' desire to compare and contrast how other aspects of their life impact their music listening behaviour. One of the largest observed differences in means was detected for users' interest in how often they skipped songs (μ_{CU} = 3.3, μ_{ST} = 4.2, $t(51)$ = 3.69, **p < 0.001**), highlighting STs' interest in behavioural habits beyond just the music that they consumed.

We posit that this elevated interest may again be due to ST users' increased exposure to data across domains. Prior work has discussed how self-tracking often propagates across multiple domains[38, 46], and the data points that are associated with music listening sessions have the potential to inform users' behaviour in other aspects of their lives. For example, understanding *location* that they have listened in or the *time of day* can inform their understanding of their daily rhythms which may be complemented by their existing self-tracking practices.

Taken together, these results clearly indicate that ST users are more interested in areas of music listening history providing further insight into their *behaviour*, specifically information connected to a *broader context*, both internally and externally.

Though the nature of this work is still exploratory, and we encourage future work to more rigorously examine these differences, this finding suggests that there are **measurable differences in how CUs and STs value data** related to their listening habits.

5 An Information Space of Music Listening Insights and Information Seeking Desires

While §4 focuses on takeaways gained from primarily Likert-style responses related to users' *data interests*, here we investigate the *abstract insights* that users sought based on analysis of their free-form text responses provided in survey section **A** as discussed in §3.1. These abstract insights can be leveraged in the design of tools to further support reflection on users' listening history and to drive research to examine what information users want to learn about themselves from their music listening behaviour.

The insights were elicited at the start of the survey to avoid influencing users' opinions with the survey content itself. Participants were also given the option to record any additional insights at the end of the survey. In total, we recorded 236 insights from 60 participants, with a maximum of 15 from one participant (p59). More than 90% were recorded at the start of the survey. We analysed these responses as detailed in §3.1 and established a consistent set of 29 codes and a further classification utilising themes and subthemes. The prevalence of these themes can be seen in Table2 and full descriptions can be seen in the codebook in supplemental material. From this qualitative analysis we generated an *information space* summarised in Fig. 11 to represent the kinds of insights users **wanted to learn** about their music listening behaviour.

5.1 Overview of the Information Space

Key elements of the information space include (i) the **User** (Fig. 11-Ⓐ) as an agent who has access to *All Available Music* (Fig. 11-Ⓑ); (ii) the collection of tracks they listen to over a set period of time – **Listening Corpus** (Fig. 11-Ⓒ); and (iii) their interactions over time with this corpus – **Music Listening History** (Fig. 11-Ⓓ).

We found that users' information needs and desires fell broadly into two categories: **Factual** and **Behavioural**, where Factual insights(Fig. 11-Ⓔ) refer to wanting to know factual information about the composition of their Listening Corpus – e.g., p4: "What's the average length of the songs I listen to?"; whereas Behavioural insights (Fig. 11-Ⓕ) sought to learn about their interactions with the corpus through their Listening History and personal preference – e.g., P9: "At what times of year do I listen more to certain songs/artists?"

These categories are not exclusive, and in the majority of instances, insights featured both factual and behavioural aspects. For example, p5: "What albums have I listened to the most?", seeking factual information about their listening corpus in the name of albums, but contextualising it through their behavioural habits by wanting to know what they had listened to the *most*.

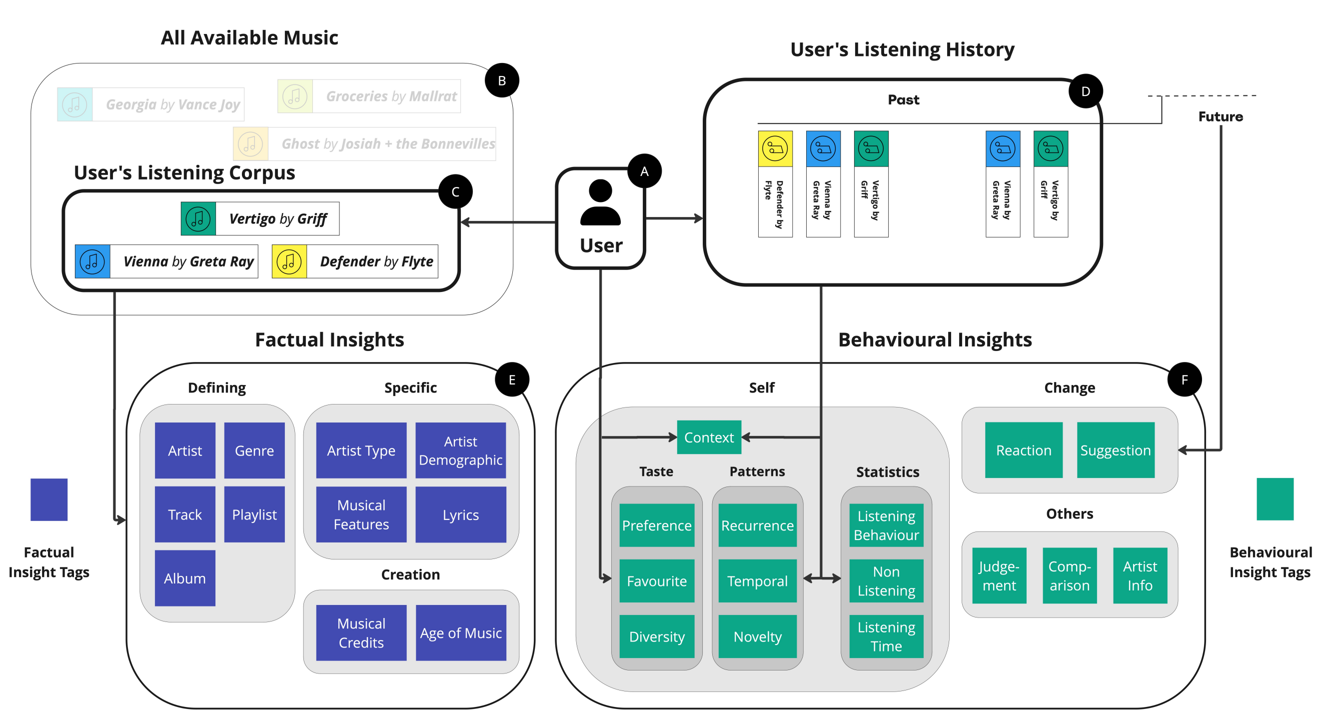


Figure 11: An overview of the information space showing simplified relationships between the user, listening history, listening corpus, and factual and behavioural insights. Connecting arrows indicate necessary relationships between different elements.

Table 2: The prevalence of different themes and subthemes in reported insights for all users and ST users

		Casual Users		ST Users	
Theme	**Subtheme**	**% of Users**	**% of Insights**	**% of Users**	**% of Insights**
Factual		98.3	81.8	100	85.5
	Defining	95	67.4	96.3	69.2
	Specific	51.7	19.5	55.6	19.7
	Creation	20	5.5	14.8	3.4
	Other Listeners	13.3	3.4	14.8	3.4
Behavioural		98.3	83.5	100	85.5
	Self	96.7	78.4	96.3	80.3
	Statistics	80	43.6	77.8	37.6
	Taste	78.3	47	85.2	55.6
	Patterns	45	18.2	48.1	19.7
	Context	18.3	5.5	18.5	6
	Others' Behaviour	16.7	6.4	22.2	6
	Change	15	4.2	14.8	3.4

5.2 Factual Insights

Factual insights (**FI**), shown in Fig. 11-Ⓔ, were primarily concerned with understanding the composition of users' listening corpus. They ranged in specificity from seeking basic, **Defining** information about their corpus, such as artist names, to deeper **Specific** information such as artists' demographic information. Table2 shows the prevalence of each of these subthemes. Around 20% of users also indicated their interest in metadata related to the **Creation** of music in their corpus, such as musical credits, or track release date. A further 13% indicated interest in learning about factual insights related to other listeners. We summarise the key findings related to factual insights as **FI1 - FI3**:

***FI1** - Genre is King.* 75% of all participants had at least one insight concerned with learning about the genre of music they consumed, in keeping with **T2** (§4.2) and the Kamalzadeh survey[31], implying users have a deep interest in the broad styles of music they enjoy (p4: "Which genres do I listen to the most?"). In contrast, less than 10% of users recorded an insight concerned with albums.

***FI2** - People DO care about specifics.* More than half of respondents indicated they wanted more **Specific** information about an aspect of their listening corpus, with 31.7% seeking artist demographic information (p38: "How many of the artists I listen to identify as Christians?") and 21.7% interested in specific musical features (p39: "What's the average length of the songs I listen to?"). The increased interest levels for ST users in specifics suggests a desire for STs to further contextualise their listening corpora and stratify along other features.

***FI3** - Age of Music is prominent.* Finally, we saw 92% of insights in the **Creation** subtheme were related to understanding how old the music they were listening to was (p48: "Is there a common time period of the music I like?"). This is of particular interest as it is not currently an area that any existing mainstream provider offers insights on (Table3).

5.3 Behavioural Insights

Behavioural insights (**BI**), shown in Fig. 11-Ⓕ, are split into non-mutually exclusive categories of insights concerning behaviour about the **Self** (reported by 97% of all participants), specific **Change** (15%) in behaviour, and about **Other** (17%) actors' behaviour.

The **Self** subtheme can be further subdivided in 4: simple **Statistics** (e.g., the amount of time listening); specific **Taste** of a user; **Patterns** or trends in listening; and the **Context** that they consumed music in.

Many of the behavioural insights are driven not only by the users' historical actions through their **Listening History** – such as understanding specific patterns of listening – but are *also* deeply connected to the **User** themselves. For example, insights that reference users' personal *preferences* rather than objective consumption data (e.g. favourite artist vs most-listened to artist). We present the 4 most salient findings as **BI1 - BI4**:

***BI1** - People are obsessed with themselves.* Unsurprisingly, we found that 96.7% of users are interested in learning about their own behaviour, in contrast 16.7% were interested in the behaviour of 'others'; 8.3% indicated explicit interest in *comparison* of their behaviour to others. We found that 22% of ST users were interested in learning about others' behaviour, compared to 12% for CUs. A small minority of STs also expressed interest in understanding the behaviour of artists they consumed, highlighting the ST desire to contextualise and gather more data about entities they interact with in order to further analyse their behaviour.

We saw an interesting emergence of *Judgement* as a specific form of insight where users would often self-judge their own behaviour (p24: "Should I expand my music range?") or consider how others might judge them (p23: "Do I look like I listen to more than one genre of music?"). This is complemented by our findings of users' occasional reticence for sharing (§6.2.5).

***BI2** - People love statistics.* Users were most interested in quantifying their listening with 80% wanting to learn about specific **Statistics** related to their listening behaviour (p12: "What is the average time per day I spend listening to music?") and 71.7% interested in general quantification of their listening – p27: "Most listened to artist". This is in fitting with our findings from **T4** where we saw users showed highest levels of data interest in generic and summary data fields.

BI3 *- When is important.* More than 30% of users were interested in learning about the temporal nature of their listening, both short-term (how it changes over the course of the day) (p13: "Which times of the day do I listen to the most music?") and long-term (how it changes over the course of many days, weeks, seasons) (p9: "At what times of year do I listen more to certain songs/artists?"). This has also seen some attention from streaming providers' overviews which have begun to illustrate **Patterns** and trends in users' behaviour (§6).

BI4 *- Context matters.* Finally, we saw interest in understanding the different contexts users listened in, both external (such as where they were physically) and internal (such as what their mood was). A subset of users also expressed interest in understanding when context drove their listening behaviour (p60: "What music do I prefer for specific fun/work occasions?") as well as when listening behaviour influenced their context (p43: "Why do I like songs that make me cry?").

Within the broader subtheme of *Change* users additionally sought to understand when music triggered certain reactions in them (p59: "Does music control my feelings or thoughts?") indicating an interest in the impact music can have on their behaviour. We also observed that users were interested in understanding how their behaviour may influence the music they listened to and what they may want to consume in the future.

5.4 A Conceptual Disconnect

To complement our finding in §4.3 that CUs and STs showed indications of differing levels of interest in specific *data* related to their listening habits, we also performed statistical tests to ascertain if there were measurable differences between the prevalence of the different themes reported in Table2. We performed Fisher's Exact Tests for each of the subthemes we had identified. Across all comparisons ($n = 11$) we found **no statistically significant differences** at the $p < 0.05$ level. This implies that **abstract information seeking desires are similar across CUs and STs**.

In combination with this finding, when establishing the space of insights that users sought, we uncovered a key disconnect between users' *data interests* and *abstract insights* where **users could identify abstract insights they wanted to gain into their behaviour, but struggled to understand the importance of the underlying data**.

The clearest example of this is in **BI3** where we observed users interest in understanding when they listened most often, and in Table2, we see 45% of all users reported wanting to learn about the temporal **patterns** in their listening. In contrast, when indicating their data interests, the average response for the time of day or day of the week when they listened to music was one of the lowest ($\mu = 3.17$ and $\mu = 2.98$ respectively), despite this being a key data field for understanding temporal patterns.

This effect was even more pronounced when comparing STs' interest in these data fields to CUs': Time of Day ($\mu_{CU} = 2.7, \mu_{ST} = 3.7$, $\mathbf{p < 0.01}$), Day of Week ($\mu_{CU} = 2.7, \mu_{ST} = 3.1$, p = 0.1). This suggests that STs – who have some experience with interacting with their personal data – may have a deeper understanding of which fields are relevant compared to CUs lending further credence to our initial finding in §4.3 that **CUs and STs have different understandings of the importance of data**, despite seeking similar abstract insights.

We saw this effect repeated as users also showed less interest in the release date of a track (**T4**) despite a prevalent theme of the information space being an interest in the age of music consumed (**FI3**). Similarly, users were not interested in data related to emotional sentiment of music (**T5**) but nevertheless discussed wanting to understand why they listened to happy or sad music (**BI4**).

This conceptual disconnect between how the underlying data relates to the insights that users want to gain suggests that even when users are aware of their available raw data, they may struggle to accurately translate it into meaningful insights.

6 Do Music Summaries Actually Serve User Needs?

Having established an understanding of users' *data interests* (§4.2) and *abstract insights* they want to gain from their listening histories (§5), we now examine whether existing yearly music summaries align with what users actually want to learn from their behaviour.

These findings are based on the capabilities of major streaming providers' 2023 overviews (Table3) and responses to questions from survey section **E** (§3.1). These responses are from 36 participants who indicated that their primary provider offered a summary of their usage (27 of these used Spotify as a primary provider). We also explored barriers that all users faced to engage more deeply with their full listening data based on responses to section **D** of the survey (§6.4).

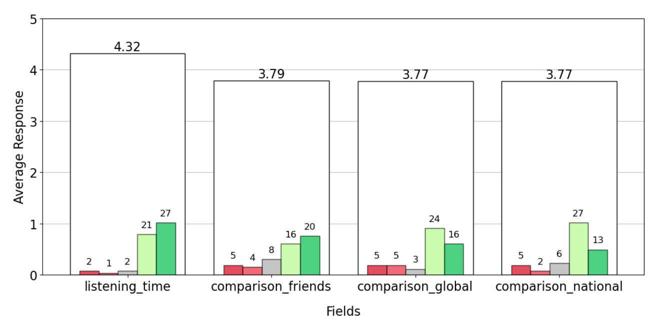


Figure 12: Responses and distributions for users' interests in insights that existing overviews provide relating to total listening time

6.1 Existing Summary Content

Through a combination of reading blog posts shared by streaming companies[20, 32, 49], sampling creators' uploads of their summaries [42, 45, 59] and the authors' own summaries, we present the first (to our knowledge) characterisation of the capabilities of existing summaries in Table3. We explore the overviews provided by

Table 3: An overview of the capabilities of existing summaries from the yearly overviews provided in 2023. *YouTube refers to 'Mood' and not genre

	Spotify	Apple Music	Tencent	Amazon	YouTube Music
Total Listening Time	In minutes (and converted as days)	In minutes	In minutes and as listener percentile	-	In minutes and as percentage of year
Top Genres	Top 5	Top 5	Top 1	-	Top 5 *
Top Songs	Top 5	Top 15	Top 10	-	Top 5
Number of Plays	Top 1	Top 15	Top 10	-	Top 1
Date First Played	Top 1	-	-	-	Top 1
Playlist of Top Songs	Yes	Yes	Yes	Yes	Yes
Top Artists	Top 5	Top 15	Top 1	-	Top 5
Total Minutes	Top 1	Top 15	Top 1	-	Top 1
Percentile of Listener	Top 1	-	-	-	1 of top 5
Listening Streak	-	-	-	-	Top 1
Top Albums	-	Top 15	-	-	Top 5
Number of Plays	-	Top 15	-	-	-
Minutes Listened	-	-	-	-	Top 1
Top Playlists	-	Top 5	-	-	Top 5
Time Listened	-	Top 5	-	-	Top 1

the top 5 music streaming providers globally – Spotify, Apple Music, Tencent Music, Amazon, and YouTube Music. Together, these represent 80% of the streaming market[17].

Table3 shows that four of the top five (Spotify, Tencent, Apple, YouTube) provide a yearly overview, whilst Amazon only provided a playlist of top songs a user had listened to. All platforms presented insights as static, non-interactive experiences.

6.2 Capabilities vs User Needs

6.2.1 Big Picture is Still Appealing. In §4.2 and §5 we saw that users were interested in summary stats based on their data interests and abstract insights. We found that that they valued the same approach in their current providers' capabilities. When asked about their interest in insights related to 'total listening time' offered by existing overviews we see a clear drop in Fig. 12 from interest in the standalone summary total listening time stat ($\mu = 4.32$) to stats about comparison ($\mu = 3.77 - 3.79$). This pattern is repeated in other areas such as Artists and Tracks too. This further emphasises the increased interest in self behaviour (**BI1**). This is generally well-aligned with the types of insights foregrounded by existing summaries via the 'top lists' that they provide.

However, since companies like Spotify pioneered yearly overviews it is hard to separate how heavily influenced participants have been by the insights they have consumed through several years of these campaigns. Users have only ever been exposed to high-level insights so it is hard to know whether or not they are interested in further info.

6.2.2 Users Want More Granularity. The depth of insight provided by these summaries is varied, with providers often surfacing higher fidelity statistics about an aspect of the overview, such as number of plays for the top song listened to. However, Spotify and YouTube *only* offer this deeper insight for the top member of a list whereas Apple presents in-depth figures for each of the entries in the lists, often providing 15 items instead of just 5 in comparison. Tencent offers somewhat deeper detail for Songs (top 10) but doesn't even provide more than just the top 1 artist listened to. Spotify consistently has the narrowest scope of factual insights with the lowest number of elements in the 'top lists' and no insights at all for albums or playlists (as of 2024).

We gauged users' interest in receiving deeper information for: just their top song, top 5 songs, or an explorable list indicating how much they had listened to all of their songs. Repeated across Artists, Albums, and Playlists we saw *very little difference* in the levels of interest across differing levels of granularity. In fact in some cases (Artists - Minutes listened, Fig. 13) we saw users indicating that they would be *more* interested in a full list ($\mu = 4.17$) than just top 5 ($\mu = 4.09$). These results imply users are happy to engage with more granular results and want more detail for artists or tracks that didn't quite make it to the top of the pile.

Although the depth of the scoping does differ across providers, they are *all* still scoped. The overview represents a snippet of a user's full history, and there is no ability to dive deeper than the information decided by the provider.

6.2.3 Users are Curious About Temporal Patterns. As we saw in **BI3** (§5.3) one of the key themes that emerged from users' abstract insights was in understanding how their listening habits varied based on the time of day, day of week, or year-over-year.

For the first time in 2023, some providers introduced some insight into temporal patterns over the year: Spotify used radial heatmaps of artist listening over the year; YouTube segmented listening into curated "seasons"; and Tencent showed the top songs in each season. However, these views are not explorable and are often stripped from shareable formats. The Spotify heatmaps were not shareable, highlighting a common theme where providers often have subtle differences between the experiential overview (what a users sees in the application) compared to the shareable overview. This again

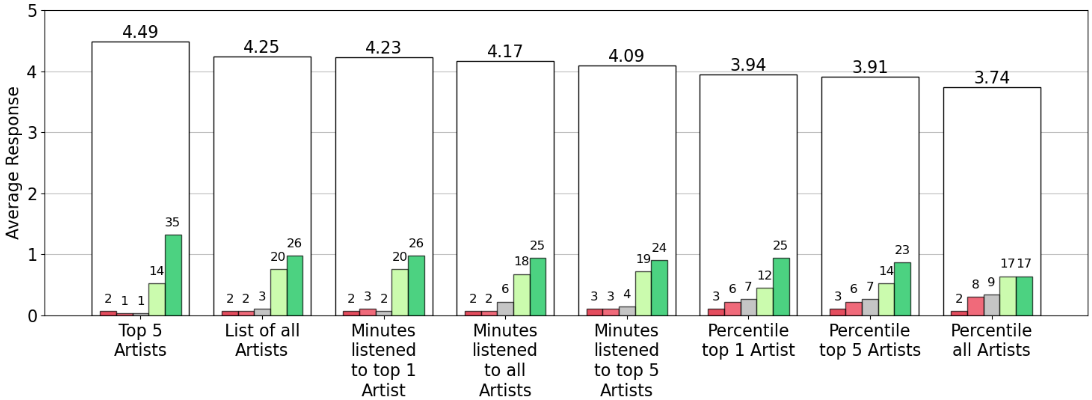


Figure 13: Responses and distributions for users' interests in insights relating to artists they have listened to

indicates a rigid approach of deciding what users can or want to see and share.

No summary currently affords users the ability to see any information about the time of day at which they listen.

6.2.4 Comparing and Sharing. We also investigated participants' desire to share their overviews with others. In general, participants **were** inclined to share, with 67% of respondents indicating they would, 22% they would not and 11% unsure. Whilst streaming providers typically facilitate sharing of overviews to large audiences, and this kind of sharing is often considered effective advertising campaigns[55], we found users were more interested in sharing with small, controlled groups of individuals than with the general public (Fig. 14).

Users also generally indicated interest in *comparison* but with some polarisation, with a subset of users actively **not** interested in comparison. Similarly to responses on sharing, those interested in comparison were most interested in comparison to their own friends (more answers of 'Very Interested').

No streaming provider currently directly offers the ability to do these kinds of comparisons to other users except obtusely through occasionally indicating the percentile of listener that you fall into, though never enabling social or friend-based comparisons.

We also repeatedly observed users indicated a desire for self-comparison – i.e. comparing how much they had listened to one artist compared to others, or from one year to the next – another feature not currently offered by any streaming provider.

6.2.5 Unserved and Underserved Interests. A common theme throughout both the *data interests* and *abstract insights* that users reported was the overwhelming popularity of **genre** as often the most interesting aspect to users **FI1**(§5.2), **T2** (§4.2). Despite this, providers offer little depth into the information surrounding genre outside of a top list. Moreover, in 2024 Spotify removed insights related to genre completely from their overviews.

In addition, existing summaries offer no information regarding specific musical features of the songs they listened to, the age of the music they consumed, or the context in which they listened, with all of these being just some of the additional areas of curiosity we uncovered throughout our survey - (**FI3**,**T5**,**BI4**).

Finally, although we touched on how Apple takes a slightly more analytical approach by presenting greater depth (§6.2.2), the theme of lack of agency is further emphasised through YouTube, Spotify and Tencent's attempts to capture less quantifiable aspects of listening such as 'listening personalities'[49] or creating personalised album covers[32] and 'art exhibitions' [20], leading towards an emphasis on aesthetically pleasing, but ultimately static graphics presenting narrative reflections of data instead of facilitating the user exploration and curiosity that we have uncovered through our work.

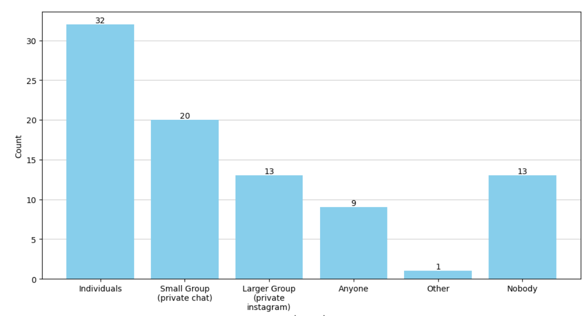


Figure 14: Who users were interested in sharing their overviews with

6.3 2024 Updates

Our findings and characterisation are based on the yearly overviews provided in 2023 as this is when we surveyed our users. We provide an updated characterisation table for 2024 in supplementary material using the same techniques[2, 11]. In general, there has been minimal change in the depth or breadth of insights offered, although Amazon now offers an overview for the first time. As noted above, the amount of information that Spotify provides has shrunken even further, providing no information on genre which we found to be a consistent favourite of consumers.

6.4 Barriers to Accessing More Information

Having seen that existing summaries only partially satisfy the interests of consumers (§6), we sought to understand what barriers exist to users engaging more fully with their music listening history in section **D** of the survey (§3.1). Most major providers now make it possible to download complete listening histories from multiple years.[5]

Ultimately, we found that the vast majority (82%) were simply **unaware of the availability** to download their full data, 42% would be interested in accessing it, and 23% indicating they may be interested. 32% of users who wanted to access their history had **no specific goals** in mind and were **more interested in exploring**. 28% wanted to utilise it to **build playlists** or **look up songs** from certain periods of time.

For those potentially interested, the main reason for reticence was concern over difficulty accessing and interacting with the data, a sentiment echoed by users who indicated they were not interested in accessing. This is tightly connected to the **conceptual disconnect** that we outlined in §5.4. Not only do most users face difficulties with regards to tech literacy in accessing or manipulating the data, but even when they know the abstract insights that they seek, they struggle to identify the specific data that is of importance to answer these questions.

All of this culminates in a class of users who are unable to meaningfully engage with their listening history data and suggests that simply increasing data access alone is insufficient. Summaries and future research must help bridge the gap between data and insight for more casual users.

7 Expanding Personal Informatics

Throughout this paper we have explored the **domain specific** aspects of users engaging with their personal data in the context of music listening by exploring their *data interests* (§4), the *abstract insights* §5 that they sought, and the ability of existing summaries to meet these desires (§6). In this section we explore how these findings could potentially be applied **more broadly to personal informatics** to expand its reach in terms of domain, users, and use cases. This discussion is intended to be forward-looking and challenge the norms of existing PI models. It is designed to offer directions for future work to investigate and apply these concepts more rigorously.

We begin by first outlining how the information space we introduced in Fig. 11 could relate to other domains with similar characteristics. We then offer a provocation which proposes how existing frameworks can be updated, shifting their focus to account for different users and use cases in domains that are not necessarily as aligned with the traditional focus of personal informatics.

[5] https://support.stats.fm/docs/import/spotify-import/

7.1 Applying the Information Space to Other Domains

In §2 we detail how the concepts we focus on in this work (**Casual Users**, **Passive Data**, and **Episodic Reflection**) are not unique to the domain of music listening. Complementing this existing work, here we discuss a potential shift in personal informatics, where users who have not typically engaged with their personal data begin to interact with data they may not even be aware was recorded as a result of (i) the rise of periodic summaries generated by service providers and (ii) collection of data with *no additional burden* on the user.

We have shown through our work that users – both casual and with self-tracking tendencies – have a desire to gain insights from this passively collected data in the music listening domain that goes beyond what is offered in existing overviews. Here we illustrate how the *information space* that we introduced in Fig. 11 could be applied across a range of domains that share similar characteristics.

In Table4 we outline how the core concepts from our information space – the **corpus** (complete set of recorded data), **history** (temporal interactions with the corpus), and the **user** (intrinsic data about the self) could be applied to explore both **factual** and **behavioural** insights across multiple domains.

In our additional example domains of fitness, financial, and screen-time tracking we detail how the three key foci of this paper are also present:

Casual Users. Prior work in the fitness domain[58] has detailed a diverse range of user involvement, from **Casual Users** – such as those who utilise wearables but don’t engage with the captured metrics – to more committed users who manually record workout data. We suggest that our specific CU and ST distinction may help to articulate these differences in future work beyond music listening.

Passive Data. Automatic recording and the shift to off-device storage means that **passive data** is also prevalent across many activities: financial transactions, location traces, and screen-time usage are frequently captured as by-products of the activity themselves. Prior work has touched on this automatically collected data and how it co-exists with more intentional forms of data collection [6, 36], but users or domains where this is their *only* form of data collection remain under-studied.

Episodic Overviews. Across these domains, provider-curated **episodic overviews** have become increasingly popular[16] and we list examples in Table4. The temporality and interactivity of these overviews is often variable with the fitness tracking app Strava offering yearly and monthly overviews[50] often coinciding with the kinds of **behavioural insights** users might seek, whilst also offering **factual insights** into historical best efforts. In contrast, screen-time reviews are often weekly and allow a greater amount of interactivity and exploration.

We saw that CUs in our study exhibited a conceptual disconnect between understanding the value of specific data – §5.4 – and that users were unaware of even being able to access their data – §6.4. As a result, these provider-curated overviews increasingly represent CUs’ only interactions with their data and their awareness of what is available. Our information space can help to make sense of these

Table 4: An overview of how our information space and concepts can be applied to other domains

Domain	Data Collection	Corpus	History	Factual Insights	Behavioural Insights	Episodic Overviews
Music Listening	Typically exclusively passive collection by music streaming providers	Library of music consumed	Stream of songs listened to	Who is my top artist?	What time of day do I listen most?	Spotify Wrapped Apple Music Replay YouTube Recap
Fitness	Combination of passive metrics (e.g. heart rate) and manually-initiated data (e.g. recording specific activities)	All completed fitness activities	Stream of where and when activities were completed	What is my best 5k time?	Do I swim faster in summer?	Strava Year in Sport Apple Fitness Trends
Financial	Fully passive record of all transactions with card or account. Mixed user-initiated and system-supported tracking through spreadsheets and tracking apps	All transactions	Spending flow over time, balance after each transaction	How much have I saved total?	Am I hitting my budget every month?	Credit Card Spending Categories Budgeting App Overviews Loyalty Card Yearly Overviews
Screen-Time	Almost exclusively passively collected by phone operating system - manual tracking cumbersome	Time spent per app or category, notifications, unlocks	Day-by-day / hourly usage	What is my most used app?	How much do I use my phone during the evening?	Weekly report from phone operating system

data interactions and support the design of systems that provide richer insight opportunities, especially for CUs.

The concepts and information space may provide a language for helping to describe diverse user types and interaction modes across passive-data domains. Prior PI work has explored how exploratory representations can support deeper forms of reflection[8, 26], however narrative overviews tend to constrain users' ability to ask questions of their own data. Driven by our findings in the music listening domain, we argue that **narrative overviews largely do not afford users the curiosity and exploration that they desire**.

7.2 A Provocation: Rethinking Frameworks for Passive, Casual, and Episodic Personal Informatics

As discussed in §2, existing models of personal informatics (Fig. 2) have richly characterised how QS users engage with their data, especially focusing on the early stages of the data lifecycle (*Collecting, Integrating*). However, these models presuppose *active, intentional tracking*, **direct interaction** with data and *frequent, cyclical engagement.*

Choe et al.'s 2015 work investigated the later stages (*Reflecting* and *Acting*) by deriving a characterisation of the kinds of visualisation insights QS users sought from personal data[7]. These findings were based on insights users had **already discovered** directly linked to their data and were presenting at QS meetups. This aligns with broader research that examines different forms of reflection[26] and the impact of interactivity and exploration on this reflection[8]. However, this relies on a user having access to their data and the agency to be able to explore it.

In contrast, our work surfaces an emerging and under-examined class of data interactions: those involving **casual users** engaging with **passively collected data** through **episodic, system-driven overviews**. These users often do not actively seek data about their consumption and may be unaware of data being recorded in the first place. This is evidenced in our study by 82% of users being unaware of the availability of their data (§6.4). We posit that for many users in music listening and beyond, the first time they are aware of the existence of this data is when presented with a curated overview with no ability to explore or query beyond the narrative confines of this summary.

This shift presents a challenge to existing frameworks as these users and use cases do not fit into the existing understanding of frequent iterative engagement with data with often clear goal-oriented outcomes[23, 35]. We have shown through the lens of music listening that casual users do seek abstract insights into their behaviour but lack the ability to satisfy their curiosity due to a multitude of factors. Moreover, there is minimal understanding of how these users even conceptualise their data interactions and whether they impact them outside of the experiential aspect of viewing their summaries. These users and use cases are not edge cases. In addition, prior research has shown that CUs do not want to engage in active self-tracking behaviour[44], and even dedicated self-trackers suffer from issues of abandonment[1] and lapsing in tracking[23]. As the data landscape continues to evolve, particularly the prevalence of passive and ambient data collection, the need to more clearly understand how, why, and if, users engage with their personal data is growing.

We therefore offer a provocation: Current frameworks are insufficient for describing a significant and growing class of personal data experiences. New or augmented frameworks should centre data interaction itself, particularly for casual users navigating often large and unfamiliar personal datasets.

The progression of frameworks towards a more involved 'lived' sense of personal informatics[46] enabled a broadening of the understanding of users who tracked and how they engaged with and

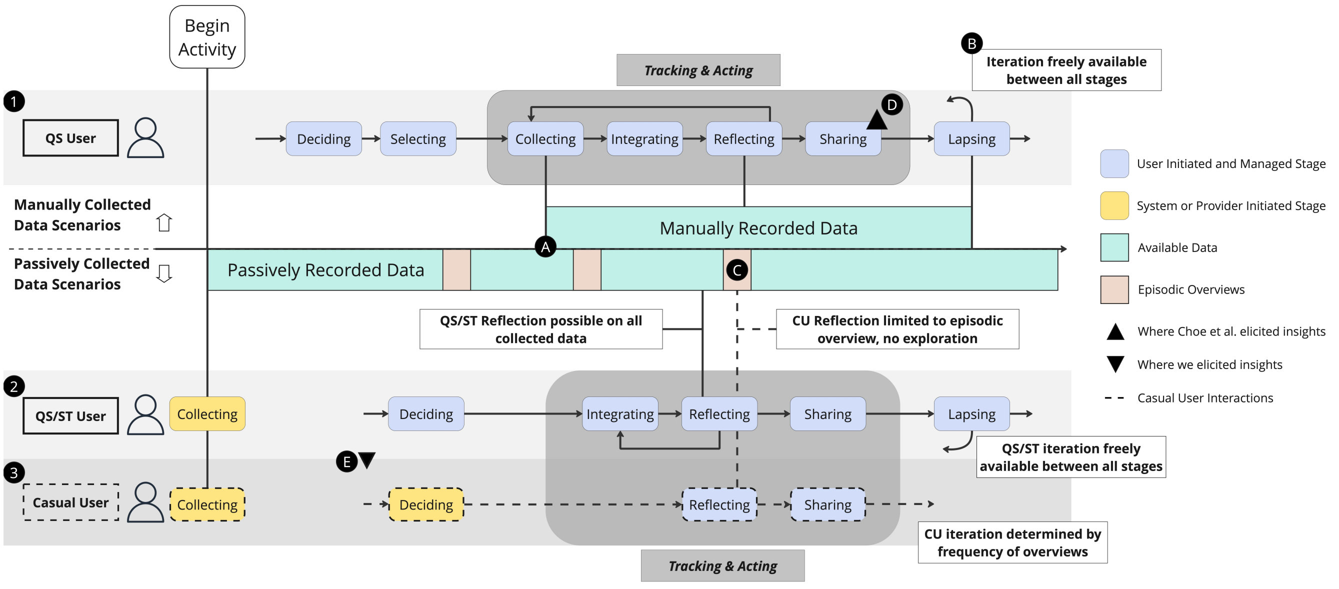


Figure 15: Our proposed augmentation of Epstein et al.'s lived informatics model of Personal Informatics illustrating differences exemplified by ① – QS Users' interactions with the stages using traditional manually recorded data ,② – QS/ST Users' stage interactions with passive data, ③ – Casual Users' stage interactions. The circled letters are referred to throughout the text.

learned from their personal data. Our provocation intends to build on this trajectory to further expand the audience of personal informatics to those who don't consider themselves trackers at all. Rather than proposing a definitive model, we intend this as an invitation to broaden PI's focus to include curiosity-driven, provider-initiated, and episodic data interactions. We outline five specific **Distinctions** that emerged through our work and illustrate them in Fig. 15.

***D1 – Active vs Passive Engagement**:* Prior models assume **active engagement** with data tracking practices, such as deciding to track, configuring tools, and managing data [23, 35]. In contrast, our users' music listening data is primarily passively collected, often without prior awareness or user intention to track (§6.4– 82% of users unaware of data), and surfaced only later. In §7.1 we outline how this extends beyond just the music listening domain. Moreover, in Fig. 15 we speculate how this impacts users' interaction with existing models and illustrate with Fig. 15-Ⓐ how **passively** produced data can result in a greater availability of data, as *collection* does not rely on conscious initiation from the user, further broadening the potential data interactions from all types of users.

***D2 – Lifecycle Engagement**:* We argue that casual users (Fig. 15-③) – such as those we observed in our study – do not engage with early lifecycle stages (e.g., *collection*, *integration*). In fact, even *deciding* to engage with their data is often system-driven. Often their only point of contact is *reflection* and possibly *action* prompted by a yearly summary.

***D3 – Episodic vs Continuous Engagement**:* Existing frameworks emphasise QS users' frequent, iterative interaction with their data to refine tracking habits over time (Fig. 15-Ⓑ)[23, 35]. In contrast, CUs may interact only intermittently – sometimes only once a year. In contrast to previous work which has looked at user-driven episodic interaction[27], we explore the cases where these interactions are initiated by the provider (Fig. 15-Ⓒ) and afford the user limited agency.

***D4 – Curated vs Curiosity-Driven Insights**:* Choe et al.'s characterisation[7] focuses on **already curated data** and the presentation of insights that these users **have already discovered** through hands-on exploration. We highlight this by showing where in existing models these were elicited – Fig. 15-Ⓓ. In contrast, in our study we captured the **curiosity** of CUs in the music listening domain to understand their **uncertain past behaviour** as they have no history of tracking their behaviour (Fig. 15-Ⓔ). This highlights the benefit of potentially augmenting these existing models to better understand and explore how passive data and episodic overviews can complement traditional quantified self users' practices and tracking habits.

***D5 - Data Exploration vs Processed Insights**:* Finally, prior work has focused on the insights that QS users were able to uncover about their behaviour during the *Reflection* or *Action* stage due to **directly exploring their data**[7, 8, 26]. In contrast, our users are limited to the **pre-processed insights** provided to them in yearly overviews which provide no ability to fully explore the level of curiosity we elicited in our study. We illustrated in §6 how existing music listening summaries fell short for the users we surveyed and theorise this could also impact multiple other domains as we speculated in §7.1.

These distinctions suggest a need to augment and adapt existing frameworks especially to better describe **Casual Users** and those who exclusively engage with **passively-recorded** data. Rather than centring only on engaged, motivated trackers, new frameworks should also account for a broader understanding of personal data interactions and for users who lack agency over their data and rely on **system-driven**, **episodic** overviews as their only form of reflection. They should account for those who stumble upon personal data and may be surprised, intrigued, or confused by what they find. Whilst these users differ markedly from dedicated self-trackers, incorporating both within a shared PI model would allow deeper understanding of these periodic interactions which are not exclusive to CUs. Moreover, it would highlight where existing models assume sustained intentionality and engagement and facilitate an understanding of the interaction and influence of a range of engagement approaches.

Our information space (§5) contributes a step in this direction, decoupling data management from insight discovery, and foregrounding how people engage with existing records of personal behaviour. We argue this shift is essential for broadening the accessibility of personal informatics and designing for **casual**, **curiosity-driven** engagement with **passively recorded data**.

8 Limitations & Conclusion

In this paper, we investigated the ways that the domain of music listening can pave the way for reshaping users' data engagement in the field of personal informatics, particularly focusing on **casual users** and **passively** collected data and how these differ from existing understandings of this space. We made **domain specific** contributions establishing users' specific *data interests* as well as the *abstract insights* they sought from their music listening before contrasting these information needs with *existing summaries* and exploring *barriers to access* that users faced for accessing further information.

Furthermore, we highlighted differences between CUs and STs and explored **broader implications** for personal informatics research by describing how existing frameworks for describing QS users' insights fall short for CUs, passively collected data, and episodic overviews. We illustrated how our information space could be applied to alternative domains and the paper culminated in a *provocation* detailing the need for the augmentation of existing models to account for the shifting landscape of passively collected data and the proliferation of episodic overviews.

We note some limitations of our work. In particular, the insights elicited in §5 are likely **non-exhaustive** as we only *required* users to record 3 insights. Whilst we attempted to achieve saturation (Fig. 3) it is still likely that the quoted percentages are **under**-estimates of the interest in different themes. In addition, some of the sub-theme codes *may* be skewed as we saw a large number of respondents indicate their interest in "What is the gender balance of artists I listen to?" in almost an exact copy of one of the example insights we provided. However, only a handful of users re-used the other 3 examples we provided, implying although interest in artist demographic may be inflated, it is still a genuine interest.

We endeavoured to recruit a representative sample, ensuring gender balance, a distribution of race, and education level. Nonetheless, all our participants were recruited from within the United States, and thus we can not draw generalisable conclusions to other populations. We urge future work to explore these themes on a larger scale and a more diverse geographic distribution of users.

Another limitation of this study was that our operational definition of STs is based on tracking behaviour in non-music domains. In §3.4 we explain the rationale for this due to the scarcity of music listening tracking behaviour in both our survey population and existing literature. Specifically recruiting users who did track their music listening data may have facilitated a more informative comparison. However, prior work has shown that users' self-tracking behaviour often expands across multiple domains and can also be reflective of their general data literacy[38] and this is reinforced by the fact that we still detected measurable differences between our two user groups – §4.3. Nevertheless, our findings should still be interpreted with the understanding that our ST/CU distinction captures *general* self-tracking orientation rather than music-specific tracking.

In addition, it is likely that some of these participants may reach the threshold of Quantified Selfer but we did not sufficiently query their data engagement habits to establish this. This may have allowed us to draw even stronger conclusions regarding the differences between QS users and CUs, however we were still able to make broader comparisons by utilising our distinction of Self-Tracking user throughout this paper.

In future work, we hope to investigate how the domain of music listening sits in a unique space within personal informatics. Despite the personal nature of the data, users still expressed interest in engaging with their data and sharing it (§6.2.5). We envisage leveraging this position, and the broad appeal of music listening to a wide range of users to explore further questions core to personal informatics – such as how to present temporal, bursty data, and how to engage casual users in the data curation process.

We hope this work and the information space we introduce acts as a foundation for considering how the changing landscape of data availability, data practices of QS and ST users, and the lessons from the music listening domain can inform how we approach data engagement for casual users in the broader field of personal informatics.

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