Investigating Everyday Music Choice on Smartphones: The Role of Personality Traits and Mood States

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Author Note

Materials, code, and data for this project are available on the Open Science Framework, under https://osf.io/rptjx/. The preregistration for this project is available under https://osf.io/7j5e3.

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Abstract

Digitalization has created an unparalleled freedom of choice in music consumption, pronouncing inter- and intraindividual differences in everyday listening behavior. To shed light on the factors involved in natural music choices, the present study collected 1,631 music-listening events from 110 participants over 14 consecutive days using smartphones for both active and passive ambulatory assessments. We obtained smartphone-sensed music-listening records and experience-sampled mood states from participants' smartphones, as well as their Big Five personality traits from traditional surveys. Using multilevel regressions, we predicted momentary music choice in terms of musical valence and energy from enduring personality traits, concurrent mood states, and their interactions. As preregistered, we expected to replicate past findings of trait- and state-congruent music choice and theory-based interaction effects. However, our models showed that personality and mood accounted only for a small fraction of variance in music choice, with one significant effect indicating that people in more activated mood states chose more energetic songs. Beyond that, our models failed to show any congruency or interaction effects for chosen musical valence and energy. We discuss methodological discrepancies to past studies as potential reasons for our lack of results and outline future avenues for smartphone-based research on everyday music choice.

Keywords: music preferences, personality, mood, smartphone sensing, experience sampling

Investigating Everyday Music Choice on Smartphones: The Role of Personality Traits and Mood States

From stationary record players to portable cassette, CD, or MP3 players and now Internet-based streaming on smartphones – technological advancements have fundamentally changed how people engage with music. This transformation has lifted previous restrictions on choice and mobility, enabling listeners to access a virtually limitless library of songs anytime and anywhere (Bull, 2005; Kuch & Wöllner, 2021; North et al., 2004). In line with the rise of music streaming, the quantity and diversity of music consumption have increased across and within listeners (Datta et al., 2018; IFPI, 2023), re-emphasizing personality scientists' longstanding objective to understand the factors involved in inter- and intraindividual music choices (e.g., Knobloch & Zillmann, 2002; Rentfrow & Gosling, 2003). Drawing on the traditional uses and gratifications approach, findings that music commonly serves for self-expression and mood regulation purposes (e.g., DeNora, 1999; Lonsdale & North, 2011; Schäfer et al., 2013) suggest that both personality traits and mood states may play a role in the musical choices people make. While these aspects were repeatedly explored individually, the current study presents a comprehensive and preregistered approach to model music choices based on enduring personality traits and fluctuating mood states. Aiming to generalize past findings to natural music-listening behavior and to gain new insights, we leverage the digital and ecologically valid shape of music listening and examine music-listening records from smartphones.

Personality Traits and Music Preferences

Personality science has long focused on interindividual differences in the music people prefer on average and how they relate to listeners' stable dispositions, that is their personality traits. Based on theories of person-environment transactions, music-listening behavior can be understood as a navigation mechanism by which individuals create or modify auditory environments that reflect and reinforce aspects of their personality (Buss, 1987; Rauthmann, 2021; Swann, 1987). In doing so, different types of music seem to serve specific uses, helping listeners fulfill various personality-related needs (Chamorro-Premizic & Furnham, 2007; Vella & Mills, 2017). Empirical studies have repeatedly supported the idea of trait-congruent music choice by linking the Big Five domains of personality to preferences for broad musical styles and granular audio characteristics in a way that matches the respective traits' conceptualization (see De Raad, 2000; Goldberg, 1990; John & Srivastava, 1999) and trait-typical uses of music (see Chamorro-Premizic & Furnham, 2007; Vella & Mills, 2017). In particular, the domain of Openness was often related to a preference for more sophisticated musical styles (e.g., Classic, Jazz; Anderson et al., 2021; Bonneville-Roussy et al., 2013; Greenberg et al., 2022; Nave et al., 2018; Rentfrow & Gosling, 2003) and songs with more negative valence, slower tempo, and lower danceability and energy (Anderson et al., 2021; Dobrota & Reić Ercegovac, 2015; Sust et al., 2023; Vuoskoski & Eerola, 2011). In support of a trait-congruent interpretation, this type of music was found to help more open listeners (i.e., those exhibiting more creativity, curiosity, and intellect) achieve an intellectually stimulating listening experience (Chamorro-Premuzic & Furnham, 2007; Vella & Mills, 2007). For the trait Conscientiousness, higher scores were associated with an aversion towards more intense musical styles (e.g., Rock, Punk) and a preference for rather unpretentious music (e.g., Pop, Country; Anderson et al., 2021; Bonneville-Roussy et al., 2013; Greenberg et al., 2022; Rentfrow & Gosling, 2003) and emotionally more positive songs (Anderson et al., 2021; Dobrota & Reić Ercegovac, 2015; Flannery & Woolhouse, 2017; Qiu et al., 2018). Such music is socially conformist and may foster productivity in highly conscientious people (i.e., those exhibiting more duty, self-discipline, and obedience to norms), contributing to trait congruence. The Big Five domain of Extraversion was repeatedly connected to an affinity for more unpretentious and contemporary (e.g., R&B,

Rap) musical styles (Anderson et al., 2021; Bonneville-Roussy et al., 2013; Greenberg et al., 2022; Nave et al., 2018; Rentfrow & Gosling, 2003) and, accordingly, more positive valence and faster tempo in music (Dobrota & Reić Ercegovac, 2015; Flannery & Woolhouse, 2021; Qiu et al., 2018; Sust et al., 2023; Vuoskoski & Eerola, 2011). Illustrating the concept of trait-congruence, songs with these characteristics may be particularly stimulating and suitable to support the social interactions of more extraverted individuals (i.e., those experiencing more positive affect and increased energy and sociability levels). For the trait Agreeableness, listeners with high scores were shown to prefer more unpretentious music (Anderson et al., 2021; Bonneville-Roussy et al., 2013; Greenberg et al., 2022; Rentfrow & Gosling, 2003) and songs with more positive valence and lower energy (Anderson et al., 2021; Dobrota & Reić Ercegovac, 2015; Sust et al., 2023; Vuoskoski & Eerola, 2011). Such songs are widely popular and have a low potential for conflict, congruent with the trait definition of higher Agreeableness (i.e., being kind, trustful, and cooperative). Finally, the trait Neuroticism was previously related to a preference for more intense music genres (Anderson et al., 2021) and songs with more negative valence (Anderson et al., 2021; Dobrota & Reić Ercegovac, 2015; Qiu et al., 2018; Vuoskoski & Eerola, 2011). Per trait-congruence, two studies indicated that this type of music supported mood regulation in people with higher Neuroticism (i.e., those experiencing more negative affect and emotional instability; Chamorro-Premuzic & Furnham, 2007; Vella & Mills, 2017).

While these individual studies have repeatedly linked overall music preferences to the Big Five domains of personality, a meta-analysis in this field revealed only small effect sizes and inconsistent patterns across studies (Schäfer & Mehlhorn, 2017), indicating that factors beyond personality contribute to listeners' preferences. Additionally, personality traits can only account for overall (i.e., average) music preferences, while momentary preferences (i.e., music choices) in everyday life vary not only between but also within individuals. Indeed, few studies have shown that between-person differences only explain 20% of the variance in daily music choices, suggesting that, beyond stable traits, fluctuating listener states play an important role in music-listening behavior (Greb et al., 2019; Greb, Steffens & Schlotz, 2018).

Mood States and Music Preferences

One state-level factor that could be linked to music preferences on a moment-to-moment basis is listeners' mood. In contrast to fully-fledged emotions, mood refers to longer-lasting affective states of lower intensity that are most pronounced as a shift in subjective feelings but not necessarily accompanied by physiological responses (Gross, 1998; Larsen, 2000). According to Russell's (1980) circumplex model, mood (along with other affective states) is defined by a valence (i.e., pleasantness) and an arousal (i.e., activation) dimension which together determine affective categories like happiness (i.e., positive valence and high arousal) or sadness (i.e., negative valence and low arousal; Watson & Tellegen, 1985).

With its ability to express and elicit various affective states (e.g., Eerola & Vuoskoski, 2012; Juslin & Laukka, 2004; Lundqvist et al., 2009), music is a popular tool to modify or maintain the valence and arousal of listeners' mood states (e.g., DeNora, 1999; Lonsdale & North, 2011; Saarikallio & Erkkilä, 2007; Schäfer et al., 2013; Sloboda & O'Neill, 2001). Hence, the music people choose to play may reflect their current mood, sparking researchers' interest in mood-dependent music choices. Past studies mainly focused on music-choice behavior during negative mood states positioned at the lower end of the valence dimension. Inspired by Mood Management Theory (Zillmann, 2015), researchers assumed that individuals in negative states would be driven to seek out pleasant experiences and would, therefore, choose songs with positive valence. From a mood regulation perspective (see Naragon-Gainey et al., 2017), such mood-incongruent music choices may act as a disengagement strategy if the music shifts listeners' attention away from the negative mood

(Miranda & Claes, 2009; Saarikallio & Erkkilä, 2007). While a few studies found support for mood-incongruent music choices (Knobloch & Zillmann, 2002; Tahlier et al., 2013), the majority of studies in this field reported mood-congruent momentary preferences in negative mood states (e.g., Chen et al., 2007; Lee et al., 2013; Taruffi & Koelsch, 2014). Several studies also found mood-congruent music choices at both ends of the valence spectrum and for the arousal dimension (Friedman et al., 2012; Greb et al., 2019; Randall & Rickard, 2017; Thoma et al., 2012; Yang & Liu, 2013). In light of Mood Management Theory, mood-congruent music choice is theoretically more challenging to explain because negative music can increase negative mood states (e.g., Hunter et al., 2010; ter Bogt et al., 2021) instead of maximizing pleasure (Zillmann, 2015). However, negative music may serve various mood-regulation functions (see Naragon-Gainey et al., 2017 for an overview of regulatory strategies). People in negative states may choose matching songs to enact adaptive engagement strategies such as problem-solving, acceptance, positive reappraisal, or as a proxy for social support (Chin & Rickard, 2012; Miranda & Claes, 2009; Saarikallio & Erkkilä, 2007). For example, the lyrics of negative-valence songs may provide information relevant to solving a distressing situation (Saarikallio & Erkkilä, 2007; Van den Tol & Edwards, 2015) or offer a sense of social sharing akin to interpersonal relationships (Lee et al., 2013; Taruffi & Koelsch, 2014; Van den Tol & Edwards, 2015). However, listening to mood-congruent negative music may also serve non-adaptive regulation strategies like venting or aversive cognitive perseveration (e.g., rumination), preventing listeners from disengaging from negative states (Miranda & Claes, 2009; Saarikallio & Erkkilä, 2007).

Personality as Moderator of Mood-Congruent Music Preferences

Because mood regulation provides a theoretical framework for both mood-congruent and -incongruent momentary music preferences (e.g., Miranda & Claes, 2009; Saarikallio & Erkkilä, 2007), the contradictory results of past studies on mood-based music choice presented above may be related to the use of different regulatory strategies. In turn, the different styles of mood regulation and, more specifically, of coping (i.e., self-regulatory attempts to reduce stress; Lazarus, 1966), were previously associated with the Big Five personality traits (Barańczuk, 2019; Carver & Connor-Smith, 2010; Connor-Smith & Flachsbart, 2007; Watson & Hubbard, 1996). According to these studies, individuals scoring high in the domains of Openness, Conscientiousness, Extraversion, and Agreeableness are more likely to use adaptive engagement strategies such as problem-solving, positive reappraisal, or seeking social support, which, as laid out above, may require mood-congruent music. In contrast, the personality domain Neuroticism seems to be positively related to employing disengagement strategies like distraction (Baranczuk, 2019; Carver & Connor-Smith, 2010; Connor-Smith & Flachsbart, 2007; Watson & Hubbard, 1996), which should call for mood-incongruent music choices. Following this rationale, personality traits may moderate the relationship between mood states and momentary music preferences.

Assessing Momentary Music Preferences

Music-listening behavior fluctuates dynamically throughout the day, making it methodologically challenging to assess music choices. Most past studies on overall or momentary music preferences relied on self-report questionnaires (e.g., Rentfrow & Gosling, 2003; Taruffi & Koelsch, 2014) or reactions to musical excerpts presented without context or after mood induction in laboratory settings (e.g., Chen et al., 2007; Flannery & Woolhouse, 2021; Greenberg et al., 2022; Knobloch & Zillman, 2002). However, self-reports of music preferences are prone to biases like socially desirable responding or memory limitations, which can be especially problematic when reporting on contextual variations of a high-frequency behavior like music choices (Baumeister et al., 2007; Stein et al., 2013). Preferences among musical excerpts, on the other hand, are restricted by the sample of songs provided by researchers, which is typically limited to very popular, artificially manipulated, or unreleased tracks and, hence, provides less choice than the natural music market (Greenberg & Rentfrow, 2017).

For an ecologically valid assessment of music preferences, researchers must investigate music choices as they naturally occur in listeners' everyday lives. While collecting behavioral data in the field has long been practically infeasible (see Furr, 2009), the digitalization of music consumption has turned digital devices like smartphones into the ideal tools to investigate music-listening behavior "in the wild." Besides radios, smartphones are the most widely used device for playing music (IFPI, 2019). Furthermore, they can collect real-time data on people's thoughts, feelings, behaviors, or environments through active and passive ambulatory assessments (see Conner & Mehl, 2015; SAA, 2018).

On the one hand, smartphones can administer the experience sampling methodology and *actively* ask participants to fill out short and identical questionnaires on repeated occasions throughout the day (Larson & Csikzentmihalyi, 2014; van Berkel et al., 2017). Previous studies have implemented this form of in-situ self-report assessment to explore momentary music choices in relation to contextual factors like mood states (Greb et al., 2019; Randall & Rickard, 2017). They repeatedly asked participants to rate the musical properties of the song they were currently listening to. These experience samplings were either randomly triggered (Greb et al., 2019), which, however, is not very efficient as people are exposed to music only in roughly 40% of randomly sampled moments throughout the day (Juslin et al., 2008; North et al., 2004; Sloboda et al., 2001), or whenever participants used a specially-developed music player app (Randall & Rickard, 2017). However, this approach only captured participants' subjective experiences, which may not always align with the objective characteristics of their selected music because the perception of musical emotion, in turn, depends on listeners' personality traits and current mood states (Hunter et al., 2011; Vuoskoski & Eerola, 2011).

On the other hand, smartphones provide a more objective way to collect music-listening data in the field via smartphone sensing, that is, the *passive* collection of smartphone usage data via custom research applications (short: apps, Harari et al., 2016, 2017; Wrzus & Mehl, 2015). Sensing apps can access a smartphone's systems logs, including the music-listening records, and unobtrusively collect music choices in everyday life, serving as a digitally-mediated behavioral observation. In contrast to experience-sampled self-reports, smartphones' digital listening records provide continuous and more granular information on selected songs. In addition, tools from music information retrieval (see Downie, 2003) allow researchers to automatically represent songs from those listening records in terms of various intrinsic musical characteristics based on their audio recordings (e.g., Flannery & Woolhouse, 2021; Sust et al., 2023; Yang & Liu, 2013). These technical audio characteristics range from basic physical parameters (e.g., tempo, pitch) to more complex aggregated features (e.g., valence, energy) learned via machine learning algorithms, which can validly represent the emotionality of music (e.g., Eerola et al., 2009; Laurier et al., 2009). While first studies have started to objectively assess and represent overall preferences displayed in natural music-listening behavior on smartphones (Stachl et al., 2020; Sust et al., 2023) or streaming platforms (Anderson et al., 2021), they considered only summary metrics, ignoring the potential of longitudinal listening records for uncovering intra-individual fluctuations in daily music choices.

The Present Study

In this naturalistic study, we investigated music choices made in everyday life and their relation to enduring personality traits and fluctuating mood states. We applied an intensive longitudinal sampling design and collected 1,631 music-listening events from 110 participants over 14 consecutive days. Using smartphone sensing, we obtained the music-listening records from participants' private phones. We extracted their momentary music preferences based on the songs they played at a given moment and represented their music choices in terms of the two computationally-derived audio characteristics of musical valence and energy obtained from Spotify.com. In addition, we administered event-triggered experience samplings to capture the valence and arousal of participants' mood states during the respective music-listening events and an online survey to assess participants' Big Five personality traits. To account for the inter- and intraindividual fluctuations in these multi-method data, we analyzed them in a multilevel regression framework predicting both the valence and energy of momentary music choices from personality traits, mood states, and their respective interactions. Based on the theoretical reasoning and past empirical findings presented throughout our introduction, our confirmatory analyses tested the following three sets of preregistered hypotheses for our music choice models.

Our first set of hypotheses concerned the role of personality traits. We expected to replicate the findings of trait-congruent overall music preferences for momentary music choices and translated the most consistent associations from the past to our two technical audio characteristics (**H1**). Specifically, we assumed that Openness would be negatively related to chosen musical valence (*H1.1a*) and musical energy (*H1.1b*), that Conscientiousness would be positively related to chosen musical valence (*H1.2a*) and negatively related to musical energy (*H1.2b*), that Extraversion should be positively related to chosen musical valence (*H1.3a*) and musical energy (*H1.3b*), that Agreeableness would be positively related to chosen musical valence (*H1.4a*) and negatively related to musical energy (*H1.4b*), and, finally, that Neuroticism would be negatively related to chosen musical valence (*H1.5a*) and positively related to chosen musical energy (*H1.5b*).

Our second research question concerned the role of mood states. We expected to replicate the mood-congruent music choices found in the majority of past studies for both dimensions of mood and based on natural music-listening behavior (**H2**). In particular, we assumed that mood valence should be positively related to chosen musical valence (*H2a*) and that mood arousal would be positively related to chosen musical energy (*H2b*).

Finally, our third set of hypotheses targeted the interaction between enduring personality traits and momentary mood states. Based on mood-regulation research, we believed that personality traits would moderate the relationship between mood states and music choices in everyday life (**H3**). More specifically, we assumed that the relationship between mood valence and musical valence would be stronger (i.e., more positive) for those with higher levels of Openness (*H3.1a*), Conscientiousness[1] (H*3.2a*), Extraversion (H*3.3a*), and Agreeableness (H*3.4a*), but weaker (i.e., less positive or negative) for those higher in Neuroticism (*H3.5a*). Complementary to this, we assumed that the relationship between mood arousal and musical energy would be stronger (i.e., more positive) for those scoring higher in Openness (*H3.1b*), Conscientiousness**Fehler! Textmarke nicht definiert.** (H*3.2b*), Extraversion (H*3.3b*), and Agreeableness (H*3.4b*), but weaker (i.e., less positive or negative) for those higher in Neuroticism (*H3.5b*). By testing these preregistered hypotheses, our study aims to replicate past findings and bring clarity to the conflicting literature on personality- and mood-based music choices based on ecologically valid real-life data.

Method

The present study was conducted within the PhoneStudy research project (https://phonestudy.org) at LMU Munich. It integrated three data collection modalities, namely online surveys, experience samplings, and smartphone sensing. All procedures have received approval from the ethics committee of LMU Munich's psychology department under the title “Moody Life” and adhered to the General Data Protection Regulation (GDPR).

[1] Please note that the subset of hypotheses in set 3 concerning Conscientiousness (H3.2a & H3.2b) was accidentally not preregistered, although we mentioned the domain in the corresponding rationale in our registration. We provide further details on all deviations from the preregistration in our OSF project.

Before data collection, all participants provided their written and informed consent, which they could withdraw at any time during the study without giving a reason.

Transparency, Openness, and Reproducibility

This study is based on data collected during a large-scale empirical project, containing various self-reported and behavioral measures. These data have not been used in any previous publication. Here, we focus our report on the procedures and measures relevant to the present research question and give a full account of all collected measures in the online supplemental material (OSM; see Chapter S1) in our OSF project: https://osf.io/rptjx/?view_only=c6c5ae723bba488e85bc5df215491f32. Thereby, we follow the Journal Article Reporting Standards (JARS) for quantitative research proposed by the American Psychological Associaction (APA).

The theoretical background, hypotheses, data preprocessing procedures, and formal analyses reported in this manuscript were preregistered under https://osf.io/7j5e3/?view_only=3ca75cb0c1324ac5be11213ecc03e07a. We made this registration after initial data collection but prior to accessing the raw self-report and smartphone-sensing data. Due to practical challenges encountered during data preprocessing, we had to make some modifications to our preregistered analysis protocol, which are detailed throughout the methods section and elaborated further in our OSF project.

This OSF project also contains datasets of our processed variables, including codebooks, which allow readers to reproduce our multilevel analyses. In line with GDPR regulations, the underlying raw data can only be accessed at the local servers of LMU Munich upon an individual legal agreement because of the privacy-sensitive nature of our data. We also provide the Python and R code for data preprocessing and analysis, along with a read-me detailing the purpose and sequence of the scripts. More information for reproducing our software environments is available in the "Statistical Software" section below.

Procedures

Our data collection took place between May and November 2020 in Munich, Germany. We recruited participants with the help of student researchers, using university mailing lists, social media, and personal contacts. To be eligible for participation, subjects had to be over 18 years old, be fluent in German, and, for technical reasons, be the sole user of a smartphone running on the Android operating system. As for compensation, participants received an individual personality profile in addition to either 10EUR or 4h of course credit, unless they decided to donate their data.

Participants were first invited to an onboarding survey where they received information about the aim and scope of the study. After providing informed consent, they installed our Android-based smartphone sensing app PhoneStudy on their private smartphones and went through a second round of informed consent within the app (i.e., granting permission access). For the following 14 days, the PhoneStudy app unobtrusively logged smartphone usage data, including participants' music-listening records (see Chapter S1 of our OSM for details and Table S1.1 for an overview of all logged data). In addition, the app administered experience samplings (ES), asking participants to report their current mood states. ES were scheduled in an event-triggered manner and appeared with a five-second delay each time participants opened a music app – as defined by an app categorization by Stachl et al. (2020) – on their smartphones. We chose this procedure to create a timely contingency between mood reports and music-listening behavior. In a concluding reactivity check, participants reported, on a scale from 1 to 5, that their music-listening behavior had been *not at all* to *barely* influenced by the event-triggered ES on average (M = 1.38, SD = 0.62). Additional ES were administered each morning, but these were not relevant to the current research question (see Chapter S1 of OSM for details). Beyond these two forms of ambulatory assessment, participants filled out two online surveys – one at the beginning and one at the end of the 14-day study period – which included demographic questions, a personality inventory, and other psychological measures that we list in our OSM (see Table S1.3 of our OSM).

Sample

We aimed to obtain the largest possible sample size given the time constraint imposed by our data collection schedule described above. The resulting convenience sample initially contained smartphone-sensing data from 476 participants. However, not all of them had listened to music on their smartphones and participated in our ES (either due to non-compliance or a misconception of our sampling schedule[2]), as discerned in Table S2 in our OSM. Hence, during pre-processing, we had to remove 363 participants with fewer than four valid *music-listening events*. We defined valid music-listening events as completed ES instances (i.e., where both mood items were answered) surrounded by a 30-minute window where a) music was played for at least one minute and b) at least one played song had available song-level information from Spotify.com. Furthermore, we removed two participants with zero variance in either of our two mood items across the ES and one participant who had not completed the personality measure. These exclusions resulted in a final sample of 110 participants with sufficient data in all measures relevant to our hypotheses. Please note that we adapted some of our preregistered exclusion criteria to preserve a reasonably large dataset without risking a loss of data quality. We report more details on the data exclusion pipeline in our OSM (see Table S2).

[2] The PhoneStudy app triggered an ES whenever participants opened a music app on their smartphone. However, many music apps provide a banner with controls (e.g., << ▶ >>) on the smartphone's lock screen, which allowed participants to start, skip, and stop songs without actively opening the corresponding music app and, hence, without triggering an ES.

The final sample comprised 75 women (67%) and 35 men (33%). Participants' age ranged between 18 and 57, with an average of 23 years (*SD* = 6.5), and the sample was skewed towards better education (78% with A-levels and 16% with a university degree).

Measures

Self-Report Measures

Personality Traits. We used the German adaption (Rammstedt et al., 2020) of the short form of the Big Five Inventory-2 (BFI-2-S; Soto and John, 2017) to assess participants' personality traits during the survey at the beginning of our study. The BFI-2-S captures the Big Five domains of personality with six items each (i.e., 30 items total). The items comprise short self-descriptive phrases (e.g., "I am full of energy and drive."), where agreement is indicated on a 5-point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (5). For each personality domain, ratings were averaged across its six items, with higher scores indicating higher trait levels. We report confidence intervals of internal consistencies for the domain scores obtained in our sample in Table 1. Consistencies for the domains Extraversion and Agreeableness were rather low with McDonald's omega point estimates of .67 and .73, respectively, which, however, is not surprising given the short questionnaire length. Overall, all consistency estimates obtained in our study were in the same range or slightly above those reported by Rammstedt and colleagues (2020).

Mood States. The PhoneStudy app captured participants' mood states via ES. In line with previous studies (e.g., Kushlev & Heintzelman, 2018; Schoedel et al., 2023), we used two single-item measures to assess participants' mood in terms of valence and arousal – the two dimensions of the circumplex model of affect (Russell, 1980). The items asked participants to report their current emotionality and level of activity at the time of the ES (see Table S.1.2 for the item wording). Responses were made on a bipolar six-point Likert scale, ranging from *very negative* (1) to *very positive* (6) for valence and from *very inactive* (1) to *very activated* (6) for arousal.

Table 1

Descriptive Statistics of State- and Trait-Level Measures

	M	*SD*	min	max	ICC	ω [$CI_{95\%}$]
Music Choice						
Musical Valence	0.47	0.18	0.03	0.97	.22	-
Musical Energy	0.65	0.17	0.00	0.99	.32	-
Mood States						
Mood Valence	4.69	0.97	1.00	6.00	.29	-
Mood Arousal	4.09	1.24	1.00	6.00	.21	-
Personality Traits						
Openness	3.72	0.75	1.83	5.00	-	.81 [.74, .86]
Conscientiousness	3.53	0.67	1.67	4.83	-	.80 [.73, .85]
Extraversion	3.14	0.62	1.50	4.67	-	.67 [.55, .78]
Agreeableness	3.86	0.60	2.50	5.00	-	.73 [.64, .80]
Neuroticism	2.96	0.87	1.17	5.00	-	.86 [.80, .90]

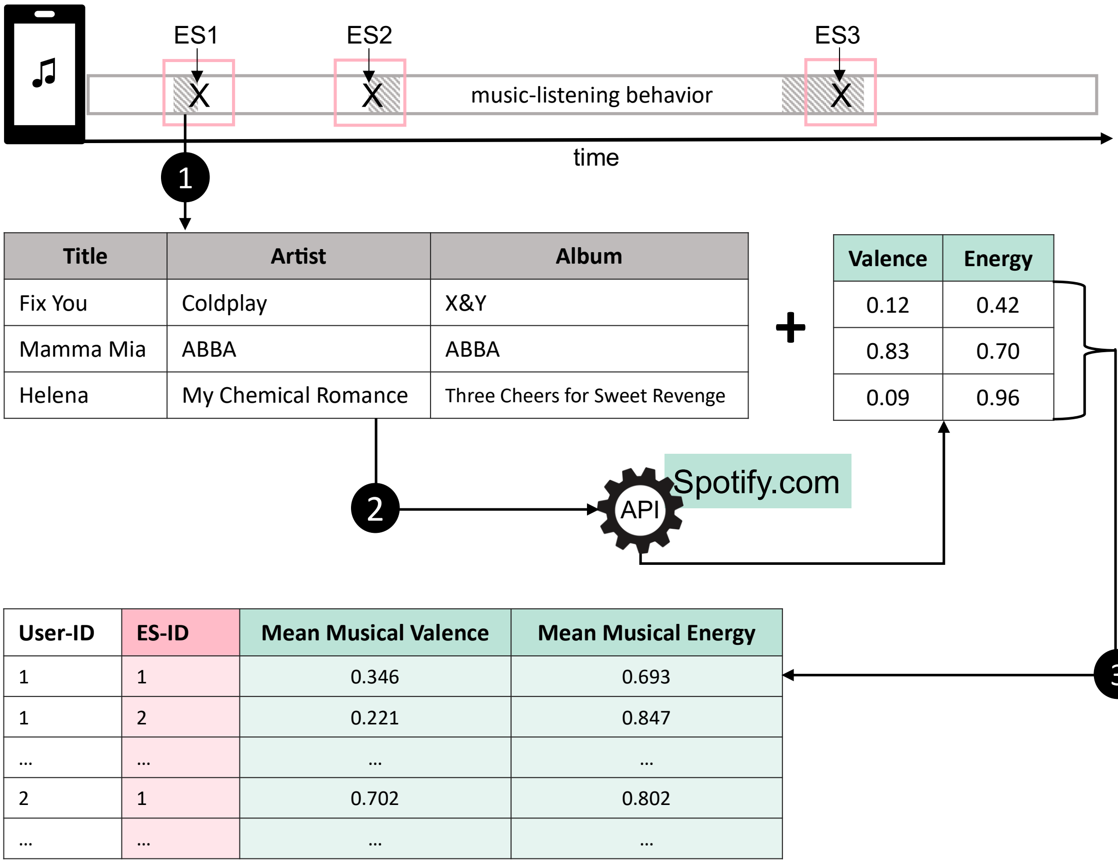
Note. N_{L1} = 1,631 observations from N_{L2} = 110 participants. Music choice was obtained from natural music-listening behavior on smartphones and coded on a continuous scale from 0 to 1. Mood states and personality traits were assessed via self-reports on a five-point (personality) and six-point (mood) five-Likert-type response scale. For both musical and mood valence, higher values indicate more positive valence. Intra-class correlation coefficients (ICC) reflect the proportion of variance of state-level measures attributable to their grouping within persons. The reliability coefficient ω refers to McDonald's omega total, calculated with the MBESS package (Kelley, 2016). The square brackets contain the 95% confidence intervals for omega coefficients.

Behavioral Music-Listening Measures

The PhoneStudy vapp provided smartphone-sensing data on a wide range of smartphone usage behaviors (see Table S1.1 for an overview), including participants' music-listening records. The app created time-stamped logs whenever participants listened to locally stored or streamed music on their smartphones. To extract momentary music choice variables from these music logs, we administered a sophisticated preprocessing pipeline described in Figure 1.

Figure 1

Preprocessing Workflow for Extracting Momentary Music Choice Variables from Smartphone-Sensed Music-Listening Records



Note. The PhoneStudy app logged song records whenever music was listened to and administered event-triggered experience samplings (ES) whenever a music app was opened. We enriched the raw song records with two song-level variables via the Spotify Tracks Application Programming Interface (API). The exemplary songs in the grey table demonstrate the face validity of the audio characteristics valence and energy (green table), whereby for musical valence, higher values represent more positive-sounding songs. More details on the enrichment are available in Chapter S3 of our OSM. Finally, we aggregated the song-level variables across all songs listened to within a 30-minute window surrounding an ES instance to represent momentary music choice in relation to the ES (bottom table).

Data Enrichment. The sensed music logs specified the title, artist, and album of participants' played songs, but lacked psychologically meaningful information about their intrinsic musical attributes. Hence, to describe participants' song choices, we enriched the raw music logs with song-level information using Spotify's Track API[3] (Application Program

[3] https://developer.spotify.com/documentation/web-api/reference/#/operations/get-several-audio-features

Interface). We visualize this workflow in steps 1 and 2 of Figure 1. For each song, we retrieved two audio characteristics that Spotify derived computationally from the respective song's audio recording (Spotify, 2023). These audio characteristics reflected the musical valence and energy of the songs in our music logs. According to Spotify, the musical valence captures the positiveness conveyed by a song, whereby songs with values closer to 1.0 sound more positive (e.g., cheerful), and songs with values closer to 0.0 sound more negative (e.g., sad, angry). In contrast, the musical energy represents the perceived intensity of a song, whereby values range from 0.0 to 1.0 and songs with higher values sound faster, louder, and noisier. We assigned both audio characteristics to the respective songs in our music logs but were not able to enrich all entries because some contained non-musical tracks (e.g., podcasts), had incorrect song information (e.g., typos in the song title), or were not covered by Spotify.com. We provide further details on the song-level data enrichment in Chapter S3 of our OSM.

Variable Extraction. To capture participants' momentary music choices in a timely contingency to their self-reported mood states, the song-level enriched music logs had to be matched with the ES instances. As the PhoneStudy app triggered ES questionnaires whenever participants opened a music app, we had preregistered to aggregate music choice (i.e., the audio characteristics of played songs) over a 30-minute window *following* the event-triggered ES. However, this rationale failed because participants often started songs through the controls banner on their smartphone's lock-screen[2], not opening their music app at all or only later to search for a specific song or to stop the music. Hence, many ES instances were preceded but not followed by music-listening behavior. To accommodate this data structure, we adapted our preregistered extraction strategy and defined music-listening events as 30-minute time windows *surrounding* an ES instance (i.e., 15 minutes before and after an ES). This definition was sufficiently broad to capture some music-listening behavior but narrow enough to still assume a timely contingency between music choices and self-reported mood states. Within these music-listening events, we removed songs played for less than 20 seconds (i.e., skipped songs) and aggregated the two audio characteristics over all unskipped songs using the weighted arithmetic mean based on the songs' playtime. The resulting variables represented participants' momentary music choices in terms of the musical valence and energy of their played songs. However, as noted above, Spotify's audio characteristics were not available for all tracks in our music logs, so the music choice variables covered only a portion of participants' played tracks. In 74% of music-listening events, the audio characteristics were available for all songs listened to, while in the remaining events, the availability of song-level data ranged between 8% and 94% of played songs (M = 69%, SD = 17%).

Data Analysis

For our regression analyses, we first adjusted extreme outliers (> |M +/- 3SD|) in our music choice variables to the value three standard deviations from the respective mean (see Winsorizing according to Ghosh & Vogt, 2012) to eliminate the influence of possible inaccuracies in our logging data. Apart from that, we did not exclude or adapt any outliers or influential cases.

To account for the hierarchical two-level structure of our data (i.e., music-listening events nested within participants), we applied multilevel regression modeling (MLMs) to test our hypotheses (Bates, Mächler et al., 2015; Kuznetsova et al., 2017). As preregistered, we computed one model for each of the two audio characteristics representing participants' chosen songs (i.e., musical valence and energy). Both models simultaneously estimated the between-person effects of personality traits (H1), the within-person effects of mood states (H2), and the cross-level interaction effects between mood and personality (H3) on momentary music choices (see Barr et al., 2013; Bates, Kliegl et al., 2015). More precisely, the MLMs contained both dimensions of mood (i.e., valence and arousal) and their interaction as Level-1 predictors, the Big Five personality domains as Level-2 predictors, and the cross-level interaction between each personality domain and the mood state focal to the respective hypothesis (i.e., mood valence for the musical valence model in H3.1-5a, mood arousal for the musical energy model in H3.1-5b). Because mood states could manifest within as well as between persons, they were within-person centered, and their person means were reintroduced as additional Level-2 predictors as recommended by Enders and Tofighi (2007). All Level-2 predictors (i.e., personality traits and aggregated mood states) were grand-mean centered. After initially running random-intercept-random-slope models (see our preregistration), we removed the random slopes to avoid problems of singular fit (i.e., variance estimates near zero; Bates, Kliegl et al., 2015). We provide our final model equations in Chapter S4 of our OSM.

To estimate the effect size of the combined predictors, we determined the models' marginal $R^2_{(m)}$, which indicates the proportion of the criterium variance explained by all fixed effects (Rights & Sterba, 2019). Furthermore, we computed fully standardized versions of the two MLMs specified above to obtain standardized regression coefficients as effect size estimates of the single predictors (Lorah, 2018). In these models, we z-standardized all variables and – after standardizing – person-mean centered Level-1 predictors. In addition to the preregistered MLMs, we also calculated some exploratory models, which we report on in our OSM (see Chapter S7).

We applied the conservative level of $\alpha = .005$ to determine the significance of our hypotheses. We derived this alpha level by correcting the default of .05 for multiple testing. Applying the Bonferroni correction, we divided alpha by the maximum number of tests necessary for any of our higher-order hypotheses, which were 10 tests for H1 and H3. Because we had preregistered the directionality of our hypotheses, we used one-tailed p-values to determine the statistical significance of the predicted effects[4]. P-values for all other effects that were not part of our hypotheses were purely exploratory and, hence, reported in a two-tailed manner. The p-values presented in our results tables below are tagged accordingly.

Statistical Software

The API call from Spotify.com was conducted in Python (version 3.8.6, Python Software Foundation, 2021), while all other steps of analysis were conducted in the statistical software R – version 4.2.1 for data preprocessing on an RStudio Server and version 4.1.2 for descriptive and multilevel analysis in a local R environment (R Core Team, 2022). For preprocessing our raw logging data on the RStudio Server, we used the packages *tidyr* (version 1.2.1, Wickham et al., 2022) and *dbplyr* (version 2.2.1, Wickham et al., 2023). We also provide an Excel file listing all R packages installed on the RStudio server in our OSF project. For the locally conducted multilevel modeling, we employed the packages *lme4* (version 1.1-31, Bates, Mächler et al., 2015) and *lmerTest* (3.1-3, Kuznetsova et al., 2017) as well as *r2mlm* (version 0.3.2, Shaw et al., 2020) to determine marginal squared *R*s. For reproducibility, we used the package management tool *renv* (version 0.16.0, Ushey, 2022) for our local data analyses and provided a complete list of all installed R packages in a renv.lock file in our OSF project.

Results

Descriptive Statistics

Across our 110 participants, we sampled a total of 1,631 music-listening events, i.e., experience-sampled mood states surrounded by music-listening behavior. More precisely, participants provided between four and 55 music-listening events, with an average of 14.83 events (*SD* = 10.36) across persons. The number of available music-listening events was

[4] Only the interaction effects regarding Conscientiousness were tested with two-tailed p-values because the corresponding hypotheses (H3.2a & H3.2b) were not formally preregistered by accident (see footnote 1).

negatively related to age (*r* = -.24, $CI_{95\%}$ [-.33, -.15]) but otherwise unrelated to demographics or personality traits. During the 30-minute window of our music-listening events, participants, on average, played 4.31 songs (*SD* = 2.38) for 11.76 minutes (*SD* = 5.99), using mostly the music app "Spotify" (89%), followed by "Google Play Music" (3%), and "Amazon Music" (3%). We report descriptive statistics on music choices, mood states, and personality traits in Table 1 and their intercorrelations in Table 2. We present correlations with demographic variables in Table S5 in our OSM.

The intra-class correlation coefficients (ICCs) in Table 1 indicate that 22% (for musical valence) and 32% (for musical energy) of the total variance of music choice measures was attributed to the grouping of music-listening events within persons. At the same time, music choices varied substantially within individuals, confirming the multilevel structure of our data.

Table 2

Within- and Between-Person Correlations Between State- and Trait-Level Measures

	Music Choice		Mood States		Personality Traits				
	Valence	Energy	Valence	Arousal	O	C	E	A	N
Music Choice									
Musical Valence	-	**.51 [.36, .70]**	.05 [-.21, .31]	.05 [-.15, .26]	-	-	-	-	-
Musical Energy	**.42 [.34, .50]**	-	.05 [-.17, .27]	-.03 [-.22, .17]	-	-	-	-	-
Mood States									
Mood Valence	-.01 [-.09, .07]	.05 [-.04, .14]	-	**.48 [.34, .63]**	-	-	-	-	-
Mood Arousal	.02 [-.05, .10]	.06 [-.03, .15]	**.41 [.32, .52]**	-	-	-	-	-	-
Personality Traits									
Openness	.01 [-.21, .21]	.06 [-.12, .26]	**.20 [.02, .43]**	.16 [-.04, .35]	-	-	-	-	-
Conscientiousness	.08 [-.09, .26]	-.09 [-.28, .09]	.12 [-.06, .32]	**.25 [.09, .44]**	.02 [-.17, .21]	-	-	-	-
Extraversion	.03 [-.18, .25]	-.05 [-.22, .15]	**.36 [.22, .53]**	**.31 [.14, .52]**	**.31 [.12, .50]**	.15 [-.04, .32]	-	-	-
Agreeableness	.08 [-.11, .27]	-.07 [-.25, .12]	.11 [-.08, .31]	**.18 [.01, .39]**	-.01 [-.21, .18]	.17 [-.03, .35]	.16 [-.03, .35]	-	-
Neuroticism	-.04 [-.29, .21]	.06 [-.16, .26]	**-.48 [-.65, -.35]**	**-.28 [-.47, -.08]**	-.11 [-.32, .06]	-.17 [-.38, .02]	**-.47 [-.62, -.34]**	**-.20 [-.39, -.02]**	-

Note. Each cell contains Pearson correlation coefficients (first row) and their 95% bootstrapped confidence intervals (second row). For correlations among state measures (i.e., music choice & mood states), coefficients below the diagonal (in black) are means of within-person correlations (with Fisher's z-transformation used for pooling), and coefficients above the diagonal (in gray) are between-person correlations (i.e., correlations between person-means of the respective states). Coefficients in bold font represent correlations whose CIs do not contain zero. For musical and mood valence, higher values indicate more positive valence.

Multilevel Models

We regressed participants' momentary music choices in terms of musical valence and energy on their enduring personality traits and concurrent mood states (see Table 3 & Table S6). Our data exhibited only minor deviations from the MLMs' distributional assumptions, against which the fixed model effects should be robust (see Schielzeth et al., 2020; Snijders & Bosker, 2012).

Table 3

Fixed Effects for Multilevel Models Predicting Music Choice from Personality Traits, Mood States, and Their Interactions

	b	*SE*	$CI_{95\%}$	*β*	*p*
Musical Valence					
Intercept	0.471	0.010	[0.45, 0.49]	-.01	.000
Mood Valence	0.001	0.005	[-0.01, 0.01]	.00	.452^
Mood Arousal	0.006	0.004	[0.00, 0.01]	.04	.107
Mean Mood Valence	0.006	0.021	[-0.04, 0.05]	.02	.774
Mean Mood Arousal	0.004	0.018	[-0.03, 0.04]	.01	.826
Openness	0.000	0.014	[-0.03, 0.03]	.00	.507^
Conscientiousness	0.006	0.015	[-0.02, 0.04]	.02	.337^
Extraversion	0.001	0.019	[-0.04, 0.04]	.00	.476^
Agreeableness	0.009	0.016	[-0.02, 0.04]	.03	.289^
Neuroticism	0.003	0.014	[-0.02, 0.03]	.01	.576^
Mood Valence x Mood Arousal	0.006	0.004	[0.00, 0.01]	.04	.199
Mood Valence x Openness	0.008	0.007	[-0.01, 0.02]	.03	.142^
Mood Valence x Conscientiousness	0.012	0.007	[0.00, 0.03]	.04	.075
Mood Valence x Extraversion	-0.012	0.010	[-0.03, 0.01]	-.04	.883^
Mood Valence x Agreeableness	-0.009	0.008	[-0.02, 0.01]	-.03	.869^
Mood Valence x Neuroticism	0.003	0.006	[-0.01, 0.01]	.01	.697^
Musical Energy					
Intercept	0.644	0.010	[0.62, 0.66]	-.01	.000
Mood Valence	0.007	0.005	[0.00, 0.02]	.04	.117
Mood Arousal	**0.011**	**0.003**	**[0.00, 0.02]**	**.08**	**.001**^
Mean Mood Valence	0.023	0.022	[-0.02, 0.07]	.08	.302
Mean Mood Arousal	-0.005	0.019	[-0.04, 0.03]	-.02	.785

Table 3 (Continued)

	b	*SE*	$CI_{95\%}$	*β*	*p*
Openness	0.010	0.014	[-0.02, 0.04]	.04	.747^
Conscientiousness	-0.013	0.016	[-0.04, 0.02]	-.05	.210^
Extraversion	-0.007	0.020	[-0.05, 0.03]	-.03	.644^
Agreeableness	-0.009	0.017	[-0.04, 0.03]	-.03	.307^
Neuroticism	0.007	0.014	[-0.02, 0.04]	.04	.311^
Mood Valence * Mood Arousal	0.010	0.004	[0.00, 0.02]	.07	.009
Mood Arousal * Openness	0.007	0.005	[0.00, 0.02]	.04	.066^
Mood Arousal * Conscientiousness	0.001	0.004	[-0.01, 0.01]	.01	.796
Mood Arousal * Extraversion	-0.011	0.006	[-0.02, 0.00]	-.05	.960^
Mood Arousal * Agreeableness	0.008	0.005	[0.00, 0.02]	.04	.047^
Mood Arousal * Neuroticism	0.002	0.004	[-0.01, 0.01]	.01	.695^

Note. N_{L1} = 1,631 observations from N_{L2} = 110 participants. Music choice was coded on a continuous scale from 0 to 1. Mood states and personality traits were coded on a six-point (mood) and five-point (personality) Likert-type scale. For both musical and mood valence, higher values indicate more positive valence. *b* = unstandardized coefficients from multilevel regression with person-mean centered Level-1 and grand-mean centered Level-2 predictors. *SE* = standard error of *b*. $CI_{95\%}$ = lower and upper bound of 95% confidence intervals around *b*. *β* = standardized coefficient from multilevel regression with z-standardized predictors (Level-1 predictors were additionally person-mean centered after z-standardizing). The regression coefficient in bold is statistically significant at a level of $p < .005$. Random effect variances are available in Table S6.1.
^ One-tailed p-values (see preregistered hypotheses and footnote 1).

For musical valence, Table 3 shows that none of the 15 included (and 10 preregistered) associations were statistically significant at the level of $p < .005$, leading us to reject all hypotheses for this criterium variable. In more detail, neither personality traits (see H1.1a-1.5a), mood states (see H2a), nor their interactions (see H3.1a-3.5a) appeared to be related to the musical valence of songs listened to. For the level-2 personality predictor Neuroticism, the regression coefficient even pointed in the reverse direction compared to our hypotheses. In line with this lack of effects, the overall proportion of variance explained by the MLM's fixed effects on musical valence was very small as suggested by a marginal $R^2_{(m)}$ of .01.

For musical energy, the results in Table 3 indicate that only one of the 15 included (and 10 preregistered) associations was statistically significant at $p < .005$. The Level-1 predictor *mood arousal* was positively related to musical energy of (b = 0.01, p = .001), which is consistent with the directionality expected in hypothesis 2 (see H2b). The unstandardized regression coefficient implies that a one-point increase in self-reported mood arousal (ranging from 1 to 6) goes along with an average increase of .01 in the played music's energy level (ranging from 0 to 1) if all other predictors are kept constant. Mood arousal also exhibited the largest effect size (i.e., standardized coefficient) with β = .08, hinting at the superiority of this Level-1 variable compared to other state- and trait-level predictors. Because no other predictor reached statistical significance, all other hypotheses regarding the musical energy criterion must be rejected. In particular, none of the Big Five personality domains (see H1.1b–1.5b) exhibited significant relations with chosen musical energy, and for Openness (see H1.1b) and Extraversion (see H1.3b), the beta coefficients even contradicted our expected directionality. Similarly, personality traits did not interact significantly with mood states (see H3.1b-3.5b), falsifying our third hypothesis. Despite the significant Level-1 predictor, personality traits and mood states only explained a very small fraction of the variance in chosen musical energy as implied by a marginal $R^2_{(m)}$ of .02. Thus, while personality and mood were more informative about the musical energy than about the musical valence of played songs, both aspects of music choice were not well explained by our predictors.

Discussion

The present study employed a longitudinal multimethod design to examine the music people select on a moment-to-moment basis on their smartphones. We extracted listeners' momentary music preferences in terms of musical valence and energy from smartphone-sensed music-listening records and predicted them from self-reported personality traits and experience-sampled mood states. Based on theoretical reasoning and past empirical findings, we expected to replicate trait-congruent associations with the Big Five personality domains (H1) and mood-congruent associations with affective valence and arousal (H2). Furthermore, we assumed that personality traits would moderate the association between mood states and music choice (H3).

However, our multilevel regression models showed that personality traits and mood states accounted only for a small proportion of variance in music choice. For musical valence, none of the personality and mood predictors or their interactions reached statistical significance, leading us to reject all hypotheses for this outcome. For musical energy, only one predictor, namely mood arousal, exhibited a significant albeit rather weak effect, indicating that people in more activated mood states prefer more energetic music, which was consistent with our second hypothesis on mood congruence (H2b). In contrast, we had to reject the remaining hypotheses for the musical energy model. In the following sections, we discuss potential reasons for this lack of effects and provide an outlook on other factors that may play a role in momentary music preferences.

Modeling Momentary Music Preferences

Our multilevel regression models showed that stable personality traits and fluctuating mood states explained only a small proportion of inter- and intraindividual variance in chosen musical valence and energy, with only one significant association. In the following sections, we discuss why our study may have been unable to replicate past findings based on natural music-listening behavior.

The Role of Personality

We found the Big Five personality domains to be largely unrelated to music choice, which contradicts past findings that repeatedly exhibited trait-congruent preferences for technical audio characteristics similar to those in our study (Anderson et al., 2021; Dobrota & Reić Ercegovac, 2015; Flannery & Woolhouse, 2021; Sust et al., 2023) and broader musical style dimensions (Bonneville-Roussy et al., 2013; Greenberg et al., 2022; Nave et al., 2018; Rentfrow & Gosling, 2003).

Because the majority of these studies assessed overall music preferences based on self-report questionnaires (Bonneville-Roussy et al., 2013; Rentfrow & Gosling, 2003) or ratings of musical excerpts (Dobrota & Reić Ercegovac, 2015; Flannery & Woolhouse, 2021; Nave et al., 2018; Greenberg et al., 2022)**,** they were low in ecological validity and, thus, their findings may not have generalized to natural music-listening behavior (Greenberg & Rentfrow, 2017). In particular, our mobile listening context may have attenuated the role of personality if smartphone-induced “auditory bubbles” (Bull, 2005, p. 344) isolated listeners from their surroundings, potentially decreasing the relevance of music for self-expression compared to self-reports or laboratory settings (e.g., DeNora, 1999; Lonsdale & North, 2011; Schäfer et al., 2013). However, these differences in study design cannot fully explain our absence of findings as two past studies successfully predicted personality traits from music choices in natural listening records using machine-learning approaches (Anderson et al., 2021; Sust et al., 2023).

Another explanation is provided in a meta-analysis by Schäfer and Mehlhorn (2017) who had previously reported only weak associations between personality traits and music preferences across studies, suggesting that our inferential models may have lacked sufficient power to detect such small effects. In support of this reasoning, our descriptive analyses demonstrated that the music selected in everyday life varied more strongly within than between individuals. With only 20-30% of the variance in music choice attributable to the grouping of music-listening events within persons, it is reasonable that stable traits like personality only account for the small interindividual variance proportion in music choice. Past studies investigating self-reported music choice on smartphones reported ICCs in a similar range and, accordingly, found that only momentary variables like listeners’ current mood or situation, but not their personality traits, exhibited significant effects (Greb et al., 2019; Greb, Steffens & Schlotz, 2018; Randall & Rickard, 2017). Hence, the contextual factors of everyday listening situations may impose musical affordances that inhibit personality congruence in music-listening behavior in the sense of the situational strength concept (Cooper & Withey, 2009; Mischel, 1977; Snyder & Ickes, 1985).

In this context, it should be noted that our study design did not consider the causal direction between personality and music choice. While it is tempting to assume an effect (however small) of the relatively stable construct of personality on music preferences (Buss, 1987; Swann, 1987), causality could also point in the other direction as people may adjust their auditory environments to their personalities or vice versa (Bleidorn et al., 2020; Rauthmann, 2021).

The Role of Mood

Our findings show that music choice was largely unrelated to mood states, except for chosen musical energy, which exhibited a positive association with listeners' concurrent arousal. Such a congruence effect was previously reported for the arousal dimension of mood (Greb et al., 2019; Randall & Rickard, 2017; Thoma et al., 2012; Yang & Liu, 2013) and may indicate that music is used to enact engagement rather than disengagement strategies of mood regulation, that is, to maintain certain arousal states instead of up- or downregulating them (i.e., to energize or relax). However, this effect was small, with a standardized beta coefficient below .10, and we could not replicate the mood congruence effects for the valence dimension repeatedly found in the past (Chen et al., 2007; Ferwerda et al., 2015; Friedman et al., 2012; Greb et al., 2019; Lee et al., 2013; Randall & Rickard, 2017; Taruffi & Koelsch, 2014; Thoma et al., 2012; Yang & Liu, 2013). Several differences in the study designs could possibly explain the deviation in our results.

First, previous studies often focused on mood congruence regarding the affect category of sadness (e.g., Chen et al., 2007; Friedman et al., 2012; Taruffi & Koelsch, 2014), while we assessed music choice and mood states in terms of valence and arousal, the two dimensions of the circumplex model of affect (Russell, 1980). As we predicted each dimension of music choice separately in one model, we could not differentiate between distinct affect categories like sadness vs. anger. If valence congruence exists only for sadness in particular, but not for negative mood in general, this operationalization may have attenuated effects. Furthermore, we modeled positive and negative valence as inversely related, whereas some researchers consider them independent (e.g., Tellegen et al., 1999). Because mood-congruent music choice was sometimes investigated only for negative but not positive valence (e.g., Chen et al., 2007; Lee et al., 2013; Taruffi & Koelsch, 2014), this aspect of our mood conceptualization may also have obscured congruency effects. However, this reasoning cannot fully account for our lack of findings because several researchers previously reported mood-congruent music choices for non-specified negative and positive valence states when operationalizing mood via the dimensional circumplex model (Greb et al., 2019; Randall & Rickard, 2017; Thoma et al., 2012; Yang & Liu, 2013). In addition, musical valence and energy correlated highly positively in our study, indicating that the dimensional approach may have indirectly represented happy (i.e., positive and energetic) vs. sad (i.e., negative and calm) songs.

A second methodological reason for our deviating results could be that we assessed natural music-listening behavior in everyday life, while most past studies investigated music choices made in listening experiments with mood induction (Chen et al., 2007; Ferwerda et al., 2015; Friedman et al., 2012; Lee et al., 2013; Thoma et al., 2012). In our ecologically more valid setting, participants, on average, listened to songs with neutral valence and slightly increased energy (examples of such songs are Coldplay's "Viva La Vida" or "Too

Lost in You" by the Sugarbabes), which aligns with the distribution of music preferences on smartphones found in another sample by Sust et al. (2023). Thus, in contrast to the song samples used in listening experiments (Chen et al., 2007; Ferwerda et al., 2015; Thoma et al., 2012), the naturally chosen songs were not prototypically positive vs. negative or calm vs. energetic, possibly reducing congruency effects. Similarly, the mood states assessed in our study occurred in mundane routine contexts and were, correspondingly, rather neutral in valence and arousal, whereas those elicited through autobiographical memory, film clips, or other induction tools may have been more intense (e.g., Chen et al., 2007; Ferwerda et al., 2015; Friedman et al., 2012; Thoma et al., 2012). Hence, the findings for mood-congruent music choices in laboratory settings may not have generalized to natural music-listening behavior in our study (see also Greenberg & Rentfrow, 2017). However, contrary to this reasoning, two studies still found the effects of mood-congruency in self-reported momentary music preferences on smartphones (Greb et al., 2019; Randall & Rickard, 2017).

While these studies had participants rate the emotionality of their played songs themselves, we used Music Information Retrieval to automatically represent smartphone-sensed song choice in terms of two technical audio characteristics. This methodological deviation could be another explanation for the lack of findings in our study because our objective audio characteristics did not capture how participants subjectively perceived songs' emotionality, which, in turn, is related to their personality traits and mood states (Hunter et al., 2011; Vuoskoski & Eerola, 2011). Furthermore, technical features cannot represent the personal meaning or memories associated with certain songs, which play a role in the emotional effects of music (Juslin et al., 2014; Taruffi & Koelsch, 2014; van Goethem & Sloboda, 2011). If mood congruence depends on subjective musical perception, our study was unable to replicate such effects.

Finally, our study's event-triggered experience-sampling scheme could also explain the discrepancies between our results and the literature. Past studies used experimental setups (e.g., Chen et al., 2007; Ferwerda et al., 2015; Friedman et al., 2012; Lee et al., 2013; Thoma et al., 2012) or assessed mood states at the onset of natural music-listening episodes (e.g., Greb et al., 2019; Randall & Rickard, 2017), so their findings may be interpreted in the sense of mood-based music preferences. In contrast, we sampled mood states whenever participants opened a music app on their smartphones, which occurred unsystematically right before, during, or after music listening, and aggregated music choices over a window surrounding these experience sampling instances. Thus, our analyses confounded the effects of mood on music choice with those of music listening on mood states, preventing any causal inferences. In particular, as music can elicit various affective states (e.g., Eerola & Vuoskoski, 2012; Juslin & Laukka, 2004; Lundqvist et al., 2009) and was previously found to return mood to neutral states (Randall & Rickard, 2017), mood states sampled after music listening may capture the effects of music instead of mood-dependent music choices. Hence, experience samplings with different timing may have captured different effects that we could not discern and that potentially canceled each other out.

Moderation Effects

With the main effects of personality and mood being insignificant or very small, it is not surprising that we found no interaction effects, indicating that none of the Big Five domains moderated the mood-congruency effects in our data. Based on empirical findings from mood regulation and coping literature (Baranczuk, 2019; Carver & Connor-Smith, 2010; Connor-Smith & Flachsbart, 2007; Watson & Hubbard, 1996), we had assumed those high in Openness, Conscientiousness, Extraversion, and Agreeableness would exhibit a stronger preference for mood-congruent music as these traits are positively related to the use of engagement-style mood regulation strategies, which, in turn, may require congruent music choices. Furthermore, we had expected that individuals high in Neuroticism would have a weaker preference for mood-congruent music since this trait is positively related to the use of disengagement-style mood regulation strategies, requiring the choice of incongruent songs. In contrast to these hypotheses and our findings, two past studies reported interaction effects inverse to our assumed directionality, namely that those higher in Openness, Extraversion, and Agreeableness tend to choose more incongruent music in negative mood states, while those higher in Neuroticism tend to select more mood-congruent songs (Ferwerda et al., 2015; Taruffi & Koelsch, 2014). As these studies investigated self-reports (Taruffi & Koelsch, 2014) and listening experiments (Ferwerda et al., 2015) instead of natural listening behavior, their findings may not have generalized to music choices made on smartphones. Alternatively, this discrepancy could also indicate that music does not serve to enact strategies like (dis-)engagement or that congruent vs. incongruent song choice cannot be automatically matched to distinct mood regulation strategies. Furthermore, individuals may apply music-based mood regulation strategies not in a dispositional way but more flexibly depending on the context in which a mood state occurs, so contextual factors instead of stable traits may moderate the association between mood and music choices. For example, listeners in negative mood states may sometimes choose congruent music to help them resolve the negative situation and, other times, incongruent music to divert their attention from the (unresolvable) negative situation.

Limitations

Our study faced several limitations that should be considered when interpreting our findings. First, our initially large sample (N = 476) was reduced to a small size (N = 110) due to a lack of music-listening and experience-sampling data, so our multilevel analyses were potentially underpowered, possibly obscuring effects (see Maas & Hox, 2005; Scherbaum & Ferreter, 2009). To obtain a larger sample size, future studies should employ an elaborate prescreening strategy to include only participants who regularly listen to music on their smartphones (see Greb et al., 2019). Furthermore, studies should improve the experience sampling scheduling and present mood questionnaires whenever participants play music and not only when they open a music app to not miss music-listening instances controlled via the banner on the lock screen. Such a design will also help disentangle the confounding effect of music listening on mood states discussed above if mood states are consistently sampled prior to music listening and if auto-regressions are considered in the modeling process.

Second, our sample composition may have restricted the generalizability of our results. As commonly the case in university recruitment contexts, our sample consisted of mostly young and female participants drawn from a Westernized, educated, industrialized, rich, and democratic (i.e., WEIRD; Henrich et al., 2010) population. Since music preferences vary by age and gender (e.g., Bonneville-Roussy et al., 2013; Greenberg et al., 2022) as well as between countries (e.g., Bello & Garcia, 2021; Park et al., 2019), follow-up studies should transfer our study design to more heterogeneous samples, which, however, have to be drawn from populations with sufficient smartphone penetration, possibly excluding, for example, certain age groups or countries. While our study's scope was also limited to owners of Android smartphones, users of different operating systems seem to not differ systematically, according to the literature (Götz et al., 2017; Keusch et al., 2020).

Third, we cannot confirm whether participants actively chose (and liked) the music they listened to on their smartphones because music apps offer various editorial, algorithmic, or user-created playlists and allow listeners to select music via the shuffle mode, which they do especially while on the go (Heye & Lamont, 2010). In particular, our participants often started playing music without opening their music apps, indicating that they did not search for a specific song but simply played what was on before. In those instances, listeners may not have been invested in their music choice, potentially obscuring personality- and mood-congruency effects. Furthermore, automated music recommendations pose a risk of listeners getting stuck in “filter bubbles” (Petridis et al., 2022), that is, overly personalized areas in the recommender space that may limit the intraindividual variance in their momentary music preferences. Hence, researchers should try to discern active choices from automatic recommendations when sensing music-listening behavior, for example, by tracking keystrokes or by explicitly asking participants about their selection mode in experience samplings.

Outlook on Music-Listening Research

The present study focused on personality traits and mood states, that is, person variables, to explain inter- and intraindividual variance in everyday music choices. However, natural music-listening behavior usually takes place in some situational context, defined, for example, by the current location, time of day, social company, and concurrent activities (Juslin et al., 2008; North et al., 2004; North & Hargreaves, 1996; Sloboda et al., 2001; Sloboda & O’Neill, 2001). Hence, to understand music choices, we should not only consider the attributes of the person but also those of their situations, as suggested by theories on person-environment transactions like the personality triad (e.g., Funder, 2006, 2009; Rauthmann, 2021). Indeed, both the objective cues (e.g., listeners’ current location or activity) and the subjective experience of situations (e.g., how dutiful or sociable listeners perceive a situation, see Rauthmann et al., 2014) were previously shown to predict momentary music choices in a way that music preferences augmented the qualities of the listening situation (Behbehani & Steffens, 2021; Greb et al., 2019; Greb, Steffens & Schlotz, 2018; North & Hargreaves, 1996; Randall & Rickard, 2017). As an underlying mechanism, different listening situations may present specific affordances regarding the uses of music (Greb, Schlotz & Steffens, 2018; North et al., 2004; Randall & Rickard, 2017; Volokhin & Agichtein, 2018). More specifically, music can serve various uses beyond self-expression or mood regulation, like pure aesthetic enjoyment, as background noise, to support physical activities such as dancing, or to create a social connection with others (Chamorro-Premuzic & Furnham, 2007; Chin & Rickard, 2012; Lonsdale & North, 2011; Schäfer et al., 2013), which, are related to situational context and require different types of music (Chamorro-Premuzic et al., 2010; Getz et al., 2015; Greb, Steffens & Schlotz, 2018; Vella & Mills, 2017). Thus, it may depend on the current situation and corresponding use of music, what music people choose, and whether personality and mood play a role in momentary music preferences. In support of this reasoning, an initial study by Greb et al. (2019) found that the uses of music listening mediate the association of music choices with mood states and situational variables.

To further explore the complex dynamics between listeners' states, situations, music uses and their music choices on a moment-to-moment basis, future studies may want to extend our approach of integrating active and passive ambulatory assessment into smartphones. Smartphone sensing not only allows researchers to objectively assess natural music-listening behavior through digital listening records but also to log various parameters of participants' listening situations from phone sensors, such as their current location from GPS, their activity from accelerometers, or their company from ambient noise (for overviews, see Harari et al., 2020; Schoedel et al., 2023). In addition, experience samplings can obtain in situ self-reports about concurrent states, subjective situation perceptions, and uses of music in timely contingency (i.e., before, during, or after) with music listening on the smartphone. In sum, smartphones provide ample possibilities for investigating the dynamic interplay of manifold variables, which will broaden our understanding of music listening behavior.

Conclusion

The present study employed a smartphone-based longitudinal sampling design to investigate momentary music choices in relation to enduring personality traits and concurrent mood states. Based on theoretical reasoning and past empirical findings, we expected that the musical valence and energy of chosen songs would be congruent with listeners' Big Five personality domains and their mood valence and arousal, with personality moderating mood-congruency. However, our multilevel regression models explained only a small fraction of variance in music choices, revealing only one significant albeit still weak mood-congruency effect indicating that listeners in more activated states chose more energetic songs. Beyond that, our models failed to replicate trait- and state-congruent momentary music preferences or interaction effects, which could be related to our study design including not only self-report based but also behavioral measures. Nevertheless, the present study introduced an ecologically valid ambulatory assessment approach to studying inter- and intraindividual differences in natural music listening behavior, which may be extended in numerous ways in future studies.

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