Determinants of Music-Selection Behavior:

Development of a Model

vorgelegt von

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ZUSAMMENFASSUNG

Für viele Menschen ist Musikhören heutzutage ein integraler Bestandteil ihres Alltags. Die Digitalisierung und technische Entwicklungen, wie Smartphones und Musik-Streaming-Dienste, bieten den Menschen fast uneingeschränkte Freiheit in jeder Situation jede Art von Musik zu hören. Im Gegensatz zur weitverbreiteten Nutzung dieser Technologien ist wenig über die Prozesse bekannt, welche der Musikauswahl im Alltag zugrunde liegen. Darüber hinaus konzentrierte sich die bisherige Forschung zum Musikhören entweder auf individuelle Unterschiede oder auf situative Einflüsse. Die vorliegende Dissertation beschäftigte sich daher systematisch mit der Frage, wie personenbezogene und situative Faktoren die Musikauswahl im Alltag beeinflussen und zielte darauf ab, die wichtigsten Faktoren beider Bereiche zu identifizieren. Außerdem wurde der Einfluss der Funktionen des Musikhörens auf die Musikauswahl untersucht. Diese Fragen und Ziele wurden mithilfe einer Online-Studie und einer Experience Sampling Studie mit Smartphones untersucht. Die Forschungsergebnisse wurden in drei wissenschaftlichen Artikeln berichtet, welche in dieser Dissertation enthalten sind.

Die Ergebnisse weisen darauf hin, dass das Musikauswahlverhalten im Alltag überwiegend von der Situation geprägt ist, in der eine Person Musik hört. Die Untersuchungen brachten detaillierte Pattern situativer Variablen hervor, welche die Musikauswahl beeinflussen. Insbesondere spielten die Funktionen des Musikhörens, die Stimmung und die Aufmerksamkeit eine wichtige Rolle bei der Auswahl von Musik im Alltag. Darüber hinaus zeigen die Ergebnisse, dass die Funktionen des Musikhörens als Mediator zwischen der Person, der Situation und der Musikauswahl fungieren. Diese Ergebnisse legen nahe, dass der Schwerpunkt der Erforschung des Musikhörens von interindividuellen Unterschieden auf situationsbezogene Einflüsse, einschließlich möglicher Interaktionen zwischen Person und Situation, verlagert werden sollte. Darüber hinaus weisen die Ergebnisse auf notwendige methodische und konzeptionelle Innovationen im Bereich der Hörertypologieforschung hin. Letztlich bieten die Befunde mehrere Möglichkeiten zur Verbesserung von Musikempfehlungssystemen.

ABSTRACT

Nowadays music listening is an integral part of many people's daily lives. Digitalization and technical developments, such as smartphones and music streaming services, provide individuals with almost absolute freedom to listen to any kind of music in any situation. In contrast to the widespread use of those technologies little is known about the processes underlying musical choices in everyday life. Furthermore, research on music-listening behavior either focused on individual differences or on situational influences. Hence, the present dissertation systematically addressed the question of how person-related and situational factors influence music selection in daily life and aimed to identify the most important factors of both domains. In addition, the role of the functions of music listening in the process of music selection was investigated. These questions and aims were approached by means of an online study and an experience sampling study using smartphones. Research findings were reported in three scientific papers, which are included in the dissertation.

The results indicate that music-selection behavior in daily life is predominantly shaped by the situation a person is listening to music. The investigations revealed detailed patterns of situational variables influencing musical choices. In particular, functions of music listening, mood, and attention were shown to play an important role in the selection of music in daily life. In addition, the results demonstrate that functions of music listening act as a mediator between the person, the situation and music selection. These findings suggest a need to shift the focus of music-listening research from individual differences to situational influences, including potential interaction effects of person and situation. Furthermore, the results suggest methodological and conceptual innovations within the field of typology research. Lastly, the findings hold several potentials to enhance music recommendation systems.

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ABBREVIATIONS

CV	Cross validation
e.g.	For example
ESM	Experience sampling method
et al.	Et alia, Latin for “and others”
ICC	Intraclass correlation coefficient
i.e.	That is
MLM	Multilevel modeling
RSS	Residual sums of squares

1 INTRODUCTION

Before the invention and dissemination of sound recording and reproduction techniques approximately 150 years ago, the only way to experience music was by performing music at home or attending live concerts or church services. Since then, technological developments of the 20th and 21st century have tremendously changed the way in which people can access, listen and engage with music. Music streaming services and portable loudspeakers now give people absolute freedom to listen to any kind of music in almost any situation of their daily life, and they are actively engaging with music to fulfill different needs in different situations. In western countries, music listening constitutes a favorite leisure activity. Compared to the ubiquity of music in society, research investigating music listening behavior in daily life remains rare. Hence, the current dissertation attempts to contribute to a better understanding of people's music listening behavior, motivated by the fundamental questions: Who listens to what kind of music in what situations and why?

This dissertation addresses the investigation of music listening behavior from a comprehensive perspective. Chapter 2 provides an introduction to research and theory related to music listening behavior and highlights open questions and challenges regarding the content and methodology of current research. Chapter 3 presents three empirical papers that have systematically addressed these open questions, and Chapter 4 summarizes and discusses research findings, offering suggestions for further research in the field.

2 Music Listening: Theory and Research

Technological developments of recent years have changed and continue to change the ways people listen to music. Specifically, the rapid growth and widespread distribution of smartphones and music streaming services enable listeners to listen to any kind of music in almost any situation (Berthelmann, 2017), actively selecting music rather than being passive recipients (Krause, North, & Hewitt, 2015). In this context, the functions of music listening—which refer to the intentional use of music to accomplish certain goals—are important. The existing research literature uses the terms *reasons for listening*, *use of music*, *goals of listening*, *motives for listening*, and *functions of music listening* synonymously. As listeners actively using music is best accounted for by the uses and gratification approach, the current dissertation uses the term *functions of music listening* as this has been most dominant in the literature (e.g., Katz, Blumler, & Gurevitch, 1973-1974; Schäfer, Sedlmeier, Städtler, & Huron, 2013).

Research investigating music listening behavior can be divided into two domains. The first consists of research dealing with individual differences of functions of music listening or of music-selection behavior. This research domain tries to explain why some people predominantly use music for emotion regulation while others mainly listen to music for intellectual stimulation, or why some mostly listen to aggressive rock music while others almost exclusively listen to melodic symphonic music (e.g., Delsing, ter Bogt, Engels, & Meeus, 2008; Gardikiotis & Baltzis, 2012). The other domain focuses on situational factors such as time, location, or current activity and their influence on music listening behavior (e.g., Krause et al., 2015; Krause, North, Hewitt, & Hewitt, 2016). The following sections will detail the findings of both domains as well as theories trying to integrate these findings. Afterwards, the outline and questions of the research conducted for this dissertation are presented. The chapter ends with an overview of methods suitable for the empirical investigation of the questions addressed by the present work.

2.1 Individual differences in music-listening behavior

A number of studies have investigated individual differences in music listening behavior and tried to explain these differences through person-related variables such as age, gender, personality traits, musical taste, or cultural differences.

Research on gender differences in music listening behavior has revealed a range of findings. With regard to the functions of music listening, research has consistently demonstrated that men tend to use music for cognitive and intellectual stimulation, while women show a tendency to use music for coping, enhancement, and to express feelings and emotions (Boer et al., 2012; Chamorro-Premuzic, Swami, & Cermakova, 2012; Kuntsche, Le Mevel, & Berson, 2016; North, 2010). Males were found to purchase and download music more often than females and attend live music events more frequently (Aguiar & Martens, 2013; Eventbrite & Media Insight Consulting, 2016).

Digital channels such as YouTube, streaming services, downloads, or online radio stations are more often used by younger people (10–34 years), and they are also more likely to access copyright-infringing music (Avdeef, 2012; Eventbrite & Media Insight Consulting, 2016; International Federation of the Phonographic Industry, 2017). People older than 30 years of age tend to use legal download sources, buy CDs, and listen to music via CD players or radio (Avdeef, 2012). Research has also indicated effects of age on musical preferences (Bonneville-Roussy, Rentfrow, Xu, & Potter, 2013; Bonneville-Roussy, Stillwell, Kosinski, & Rust, 2017), along with consistently negative associations between age and diverse functions of music listening (e.g., using music in the background while doing other activities), the amount of music consumed, and general engagement with music (Bonneville-Roussy et al., 2013; Chamorro-Premuzic et al., 2012; North, 2010).

A large body of research has investigated associations between personality traits and music listening behavior. Ferwerda, Yang, Schedl, and Tkalcic (2015) showed that personality traits (Big Five) are related to the ways individuals select music from streaming services. People scoring high on Openness to Experience lean towards mood taxonomies, while those rating high in Conscientiousness are more likely to use activity taxonomies for browsing through music offered by streaming services. In regard to the functions of music listening, Openness to Experience has repeatedly shown associations with the use of cognitive and intellectually-stimulating functions, while people scoring high on Neuroticism tend to use music for mood and emotion regulation (Chamorro-Premuzic & Furnham, 2007; Chamorro-Premuzic, Gomà-i-Freixanet, Furnham, & Muro, 2009; Chamorro-Premuzic et al., 2012; Chamorro-Premuzic, Swami, Furnham, & Maakip, 2009; Vella & Mills, 2017). In addition, numerous studies link personality traits (Big Five) with musical taste (e.g., Delsing et al., 2008; Greenberg, Baron-Cohen, Stillwell, Kosinski, & Rentfrow, 2015; Rentfrow & Gosling, 2003). Most of those studies equate liking for musical styles with frequent listening to these styles. As musical taste (measured via liking ratings for musical styles) constitutes an attitude towards music, it is not yet clear if these assumptions are correct. To date, only one study exists that has investigated the association between musical taste and actual listening behavior in daily life. Dunn, Ruyter, and Bouwhuis (2012) observed small to medium positive correlations between liking ratings for several musical styles and actual listening duration. This indicates an indirect relation between personality traits and music-selection behavior.

Research on the influence of musical taste suggests that fans of different musical styles tend to use different functions of music listening, such as fans of rock and rap music mainly using music to express their identity while fans of jazz, blues or classical music tend to use it for intellectual stimulation or to experiment with different sides of their personality (Getz, Chamorro-Premuzic, Roy, & Devroop, 2012; Schäfer & Sedlmeier, 2009). Overall, the intensity of music preference for people's favorite music shows strong associations to communicative functions of music listening such as expressing identity or values (Schäfer & Sedlmeier, 2009; 2010).

Furthermore, musically trained people are more likely to engage with musical activities (Elpus, 2018) and listen to a greater variety of styles in daily life (Stratton & Zalanowski, 2003). These findings are in line with Elvers, Omigie, Fuhrmann, and Fischinger (2015), who found a tendency of musicology students to have an omnivorous musical taste.

The findings regarding cultural influences on music listening behavior are rather diverse. Whereas some studies have found cultural associations for specific functions of music listening such as expressing cultural identity (Boer et al., 2012; Boer & Fischer, 2012), other studies did not reveal any cultural differences (Rana & North, 2007; Schäfer, Tipandjan, & Sedlmeier, 2012; Tarrant, North, & Hargreaves, 2000).

In sum, research has shown numerous associations between person-related variables and different aspects of music listening behavior. It is important to highlight that the majority of the findings discussed above rely on surveys and laboratory studies that generally do not measure real-life behavior and ignore situational influences.

2.2 Situational influences on music-listening behavior

As music listening always takes place in any kind of situation, the question arises as to how situational factors influence music listening or selection behavior. Conceptualizing a situation is a notoriously difficult endeavor. Consequently, definitions and terminologies vary considerably between different research fields as well as within the same field (for overviews see Rauthmann, Sherman, & Funder, 2015 or Rauthmann, 2015). A common approach to distinguish between situational and person-related factors in music psychology, also applied by the current dissertation, is to differentiate between time-stable (i.e., person-related) and time-varying (i.e., situational) variables. Compared to the large number of studies investigating individual differences of music listening behavior, research on situational influences is rare. However, the few studies investigating situational influences have tended to focus on listening location, activity, presence of others, mode of presentation, or time of day, and they have already produced a set of significant findings.

Research addressing listening location has consistently demonstrated that at present, people mostly listen to music at home, while driving, or using public transportation (Greasley & Lamont, 2011; Krause et al., 2016; North, Hargreaves, & Hargreaves, 2004). North et al. (2004) reported that specific functions of music listening are associated with certain locations, while Krause et al. (2016) showed that the effects of music, in situations where it cannot be controlled, are also influenced by listening location. Furthermore, listening location also seems to influence the perception of the arousing qualities of music (Krause & North, 2017).

People listen to music while engaging in numerous activities, with personal maintenance, active leisure activities, and travel being the most frequent (Greasley & Lamont, 2011; Juslin, Liljeström, Västfjäll, Barradas, & Silva, 2008; North et al., 2004; Sloboda, O'Neill, & Ivaldi, 2001). In addition, the activity performed while listening is associated with the degree of engagement with the music and also influences the perceived arousal of music in a given situation (Krause & North, 2017; Randall & Rickard, 2017). In particular, people tend to perceive music as more arousing when doing housework and as less positive when traveling (Randall & Rickard, 2017).

The functions of music listening people use differ depending on the presence of others. For example, people tend to use music to help them concentrate or to help the time pass when they are alone and use it to create specific atmospheres when together with friends (North et al., 2004; Rana & North, 2007). In addition, people who mainly listen to music alone tend to use music to fulfill emotional needs (Tarrant et al., 2000, 2000).

Moreover, time of day is an important factor influencing music listening in daily life. People use music differently throughout the day. In particular, people are more likely to use music to pass the time or to foster concentration during the workday than in the evening (North et al., 2004; Rana & North, 2007).

Several studies have investigated the effect of momentary mood on the functions of music listening and on music selection, but the findings are inconsistent. While recent research has consistently demonstrated that people tend to select music that is congruent with their current mood (Randall & Rickard, 2017; Skånland, 2013; Thoma, Ryf, Mohiyeddini, Ehlert, & Nater, 2012), this contradicts theories and research that suggest that people select music to moderate their arousal to an optimal level (Konečni, Crozier, & Doob, 1976; Konečni & Sargent-Pollock, 1976) or to reach arousal state goals appropriate for certain situations (North & Hargreaves, 2000). Further research is therefore required to clarify the specific relationship between momentary mood and music selection in daily life.

In sum, research has revealed several associations of situational factors and different aspects of music listening. Functions of music listening are influenced by several situational variables, but, to date, there has been no attempt to investigate if the broad range of situation-specific listening functions are associated with music-selection behavior. Given that musical taste has been linked to the use of specific functions on the individual level, listening functions might be associated with specific musical choices on the situational level. This would suggest a mediating role of functions of music listening between the person, the situation and the music selected. Hence, the specific role of listening functions in the process of music selection needs further clarification.

2.3 Models and approaches that integrate person-related and situational factors

Despite the large body of research discussed above, few approaches exist that integrate these findings into theoretical frameworks or models. Two approaches exist, neither of which specifically focuses on music-selection behavior.

The first model, seen in Figure 2.1, was suggested by Hargreaves, Miell, and MacDonald (2005). This reciprocal feedback model of musical response integrates many of the above-mentioned factors, but it does not specifically focus on music selection. Instead, this model rather constitutes a framework that describes several responses to music, which interact with the music, the listener, and the listening situation and context. The use of music (i.e., the functions of music listening) is indicated in the interaction between the listener and the listening situation or context. The model's main focus is to describe "the various determinants of a specific response to a given musical stimulus at a particular point in time" (Hargreaves et al., 2005, p. 7). Hence, the model does not describe the active selection process of listeners who can freely choose from a large amount of music with different styles and characteristics but rather treats the listener as a passive responder. The reciprocal nature of the model makes it challenging to see how the different variables interact or where causal processes might be involved, and empirical testing is nearly impossible. Due to these limitations and the fact that the model aims to explain passive responses to music, it could not be used for the present work that aimed to explain active music selection.

The second model, suggested by Randall and Rickard (2017), was released during the course of the present work and published at the same time as the first paper of the current dissertation. This model of personal music listening integrates a number of the influencing factors discussed above, specifically incorporating person-related and situational variables (see Figure 2.2.). The model also accommodates functions of music listening (specified as reasons for music listening) on both levels, indicating that functions of music listening can be influenced on the situational level by context and

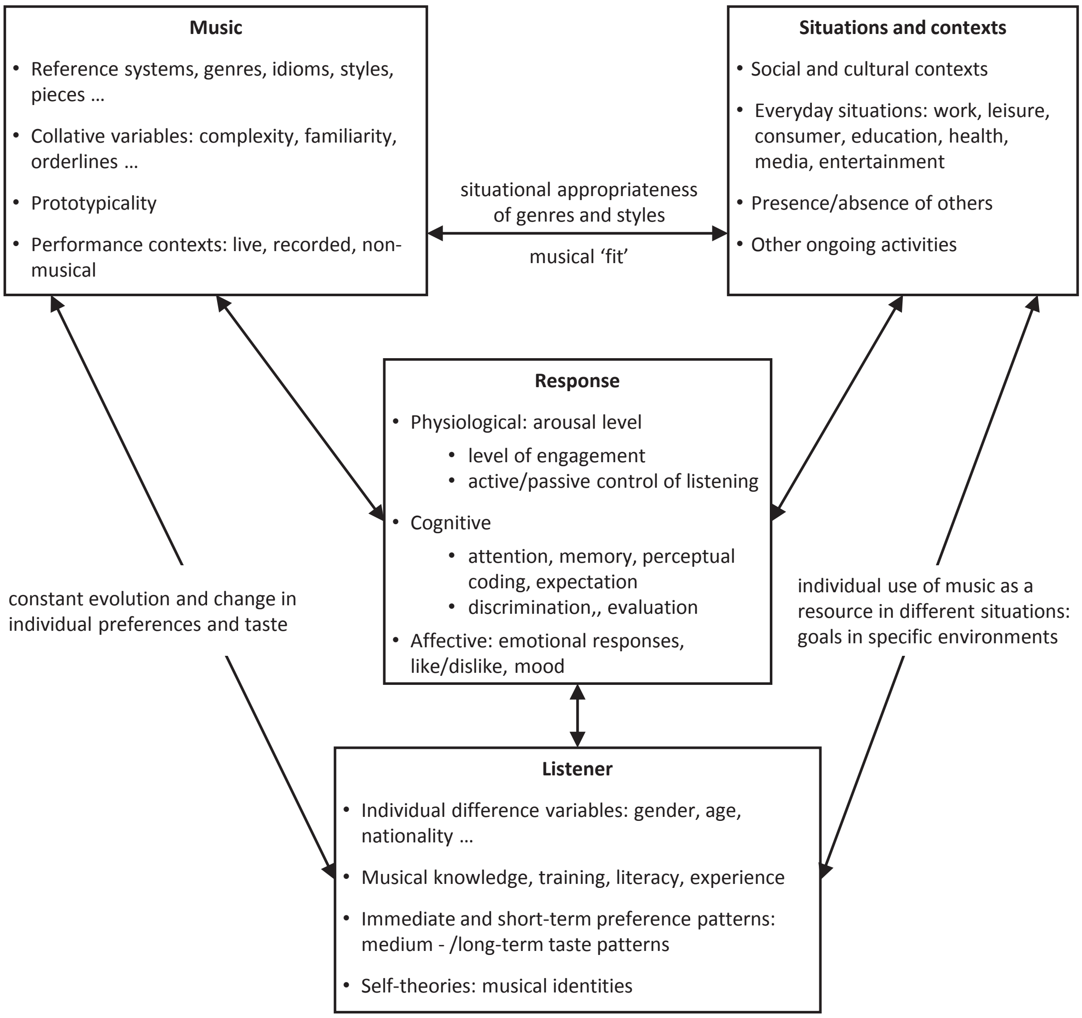

Figure 2.1. Reciprocal feedback model of musical response (Hargreaves et al., 2005).

initial mood and on the listener level via demographics, personality, and health and well-being variables. In contrast to the reciprocal feedback model of musical response, the model by Randall and Rickard (2017) includes active music selection that is influenced by person-related and situational variables. Since people actively select music to accomplish certain goals, it remains unclear why the reasons for listening in this model do not influence music selection. Following the idea of active music selection as discussed above, reasons for listening should be assumed to have a significant impact on music selection. Furthermore, the model exclusively focuses on music listening via headphones and aims to explain emotional responses to music. This differs from the aim of the present dissertation, which is to explain music-selection behavior in daily life in general, without specifically focusing on listening via headphones. Given its recent publication and the criticism outlined above, this model could not be used for the present dissertation.

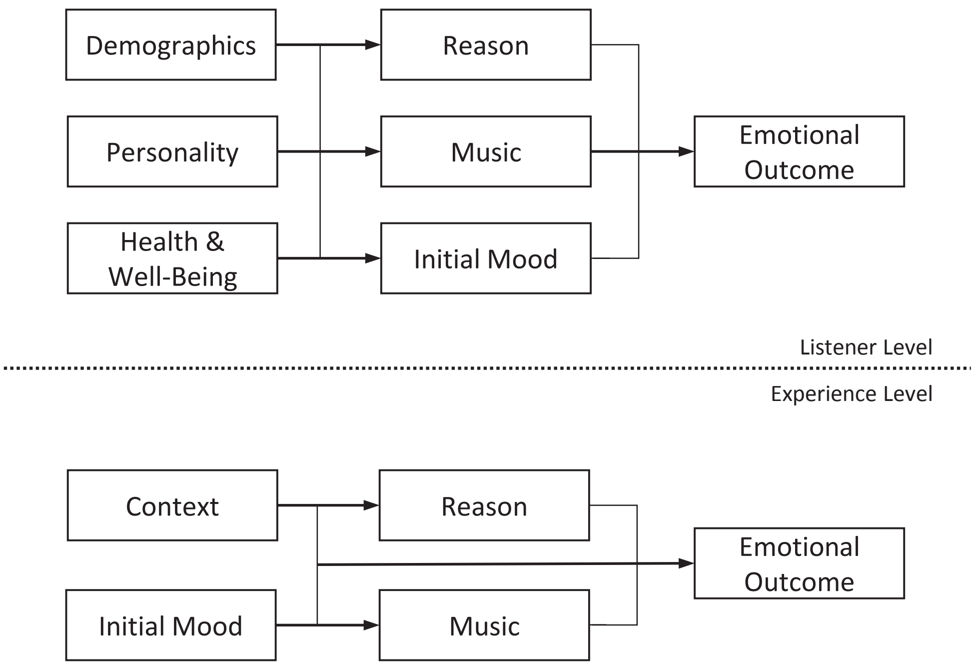

Figure 2.2. Theoretical model of personal music listening (Randall & Rickard, 2017).

2.4 Outline of present research

So far, there have been numerous research findings on the multitude of factors that influence music listening and music-selection behavior. The theoretical models by Hargreaves et al. (2005) and Randall and Rickard (2017) are two attempts to explain how these factors interact. However, none of the models specifically addresses music-selection behavior. For example, the model by Hargreaves et al. (2005) treats the listener as a passive responder to a given stimulus at a specific time, thereby largely ignoring that people actively select the music to which they wish to listen. Randall and Rickard (2017) exclusively focus on listening via headphones and on explaining emotional responses to music. Even though the authors integrated music selection into their model, it remains unclear why reasons for music listening are not assumed to influence music selection. Furthermore, the authors named their model the theoretical model of personal music listening, but it exclusively focuses on emotional responses. Although emotion and mood regulation is a prominent function of music listening, it only constitutes one of many functions music listening can fulfil (for an overview of possible functions see Schäfer et al., 2013). As modern-day listeners actively select music in specific situations, the question of how these musical choices are shaped by the person and the situation is not adequately addressed by current research. Never before have people been more actively involved in the process of music selection. Hence, the need to understand the processes and mechanisms underlying these active choices is evident. Given the limitations and controversies of the two existing models discussed above, the research of the present dissertation was guided by the process model of music selection, depicted in Figure 2.3.

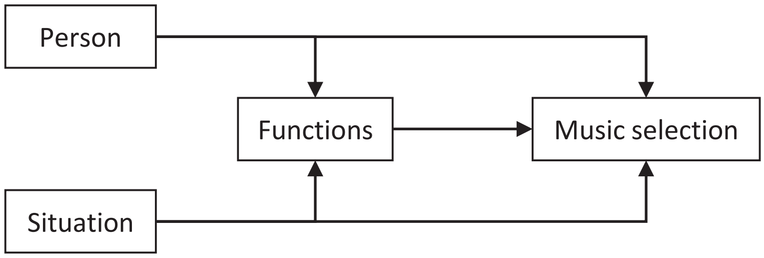

Figure 2.3. Process model of music selection.

The model contains the person, the situation, and the functions of music listening as the main factors influencing music selection. Person-related variables (i.e., all variables discussed in Chapter 2.1.) can influence the functions of music listening and music selection. For example, people who enjoy electronic dance music might tend to listen to music for dancing and also might tend to listen to faster and more rhythmic music than others do. The situation is suggested to have possible direct effects on functions of music listening as well as on music selection. As people currently actively choose music, the functions of music listening are expected to play an important and mediating role in music selection. For instance, music might be used differently over the course of a day, such that in the morning it might be used to wake up and energize, while it is used to calm down and relax in the evening, resulting in diverse musical choices. Most studies described in Chapter 2.1 and 2.2 either investigated person-related or situational variables, focusing mainly on bivariate associations, whereas in real-life situations, all aforementioned factors of music listening appear simultaneously. Therefore, to best reflect the complexity of real-life situations, it was of great importance to consider variables from both domains concurrently. This would also allow investigation of the relative impact of person-related and situational factors.

Following the proposed model, the major questions of the current work were as follows:

1. How strong is the relative influence of person and situation on a) functions of music listening and b) music selection?
2. What are the most important person-related and situational variables predicting functions of music listening and music selection in daily life?
3. How stable are situational effects on the functions of music listening and on music-selection behavior across different listeners?
4. Do functions of music listening act as a mediator between person, situation and music selection?

To address these questions, both an online study and an experience sampling study were conducted. The online study asked participants to report three self-selected listening situations in which they typically listen to music. For each situation described, participants reported on situational characteristics (e.g., mood, presence of others), functions of music listening in the specific situation, and on the music selected. Also, person-related variables (e.g., Big Five, musical taste) were collected. The experience sampling study monitored participants' listening behavior for 10 consecutive days while asking them 14 times a day if they were listening to music. For each music listening situation, participants also reported on the situation, the functions of music listening, and the music to which they were listening.

The three empirical papers presented in the third chapter of the current dissertation systematically investigated the suggested effects of the proposed process model of music selection. The first paper addresses the direct effects of person-related and situational variables on the functions of music listening and the development of an inventory that measure the functions of music listening in daily life. The second paper explores the direct effects of person, situation, and functions of music listening on music-selection behavior while simultaneously implementing a novel analysis strategy based on statistical learning (see Chapter 2.5). Finally, the third paper is concerned with the prediction of music-selection behavior in daily life while additionally testing the assumption that functions of music listening act as a mediator between the person, the situation and music selection. The first two papers are based on the data of the online study, while the third paper uses data retrieved using the experience sampling method. In addition, a significant portion of the empirical papers is concerned with the introduction of new statistical methods into the field of music psychology. The motives for these efforts are outlined in the following sections.

2.5 Suitable methodology

To properly address the questions outlined in the preceding section, several methodological challenges had to be considered. These challenges and their solutions are detailed here.

2.5.1 The need to consider within-person variance and the use of multilevel modeling

The questions concerning the relative influence of person and situation on music-selection behavior was associated with specific methodological preconditions regarding research design and subsequent statistical analysis. Most studies discussed in Chapter 2.1. are based on survey or laboratory data usually obtained by asking participants to answer general questions or statements about music, such as "Listening to music really affects my mood" (Chamorro-Premuzic & Furnham, 2007, p. 179) or "I listen to music because …" (Schäfer et al., 2013, p. 5). This type of research design only allows for the investigation of individual differences between participants. If the aim is to investigate situational and person-related influences on music-selection behavior simultaneously, it is necessary to collect multiple measurements for each participant in different situations. This allows the investigation of between-person (person-related) and within-person (situational) variance. Accordingly, data points are not independent as several measurements pertain to a single person. This nested data with two levels of variance is best accounted for by using multilevel linear models (also called hierarchical linear or mixed models). Regarding the questions of the present work, these types of models have several benefits. First, they allow for estimates of the amount of variance in the outcome variable that is attributable to the various levels involved. Second, they enable the researcher to model predictors of different levels (i.e., situational and person-related in the present case) simultaneously. Third, they allow estimates of group-specific deviations from overall mean effects. These benefits will be outlined in the following section (cf. Snijders & Bosker, 2012).

For the estimation of variance components, the simplest model, namely a model only containing an intercept for each group, is used. These models are usually referred to as “intercept-only”, “totally unconditional”, or “null” models and are defined by

$$Y_{ij} = \beta_{0j} + R_{ij} \tag{2.1}$$

In this model, Y_{ij} denotes the outcome for the *i*th Level-1 unit (e.g., situation) of the *j*th Level-2 unit (e.g., person), and R_{ij} denotes the residual of Level 1. This model estimates an intercept (β_{0j}) for each Level-2 unit following the equation:

$$\beta_{0j} = \gamma_{00} + U_{0j} \tag{2.2}$$

where γ_{00} denotes the grand mean of Y and U_{0j} denotes a unit-dependent deviation. Substituting Equation 2.2 in 2.1 yields the overall model formula:

$$Y_{ij} = \gamma_{00} + U_{0j} + R_{ij} \tag{2.3}$$

This model can then be used to decompose variance components by calculating the intraclass correlation coefficient (ICC) ρ. The two terms $U_{0j}$and R_{ij} in Equation 2.3 are assumed to vary around 0 (i.e., to have a mean of 0), and their variances are denoted by $\sigma_{u_0}^2$ and σ_r^2. The ICC is given by:

$$\rho = \frac{\sigma_{u_0}^2}{\sigma_{u_0}^2 + \sigma_r^2} \tag{2.4}$$

As $U_{0j}$and R_{ij} are the only sources of variation in Equation 2.3, the sum of their variances ($\sigma_{u_0}^2 + \sigma_r^2$) equals the total variance of Y_{ij}. Hence, the ICC as given by Equation 2.4 specifically indicates the amount of variance that is attributable to Level-2 units of the data, while the rest is attributable to Level-1 units. The ICC constitutes an important indicator in the current work as it was used to estimate the relation of person-related and situational influences on functions of music listening and music-selection behavior.

Furthermore, the separate equations for each level enable the integration of predictor variables pertaining to different levels. Presuming one predictor variable for each level (*x* and *z*), these could simply be added to Equations 2.1 and 2.2:

$$Y_{ij} = \beta_{0j} + \beta_1 x_{ij} + R_{ij} \tag{2.5}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01} z_j + U_{0j} \tag{2.6}$$

In these equations, an additional regression coefficient (β_1, γ_{01}) is estimated for each predictor. As β_1 and γ_{01} are assumed to be the same for all Level-2 units, they are called fixed coefficients or fixed effects. Here, it is important to understand that the predictor x in Equation 2.5 exclusively explains variance on the first level, while the predictor z exclusively explains variance on the second level. To give a concrete example in the context of the present work, the model given by Equations 2.5 and 2.6 could be used to investigate the association between the tempo of music selected (measured on a continuous scale from slow to fast) and situation-specific arousal (Level 1) and liking for electronic dance music (Level 2). In this example, the tempo of the music selected in a situation i by person j would by be denoted as Y_{ij}, while arousal of person j in situation i would be denoted as x_{ij}, and the person-related variable liking for electronic dance music would be denoted as z_j. Hence, Equation 2.5 could determine if situation-specific mood is associated with the selection of slower or faster music, while Equation 2.6 could show if people with higher liking ratings for electronic dance music generally listen to faster music (i.e., have a higher individual intercept) or vice versa.

Finally, multilevel linear models also allow for slopes at Level 1 to vary by Level-2 units. A simple two-level model with one predictor variable at Level 1 is given by:

$$Y_{ij} = \beta_{0j} + \beta_{1j} x_{ij} + R_{ij} \tag{2.7}$$

In this model, for each Level-2 unit, an intercept β_{0j} and a regression coefficient β_{1j} is estimated. While β_{0j} is given by Equation 2.2, β_{1j} is given by:

$$\beta_{1j} = \gamma_{10} + U_{1j} \tag{2.8}$$

where γ_{10} denotes the overall mean effect and U_{1j} denotes unit-dependent deviations. In the current dissertation, these models were used to identify whether situational effects on music selection varied between individuals.

2.5.2 Benefits of statistical learning for variable selection

The current dissertation followed a comprehensive approach in modeling music-selection behavior by taking into account a large set of potential influencing factors. Consequently, variable selection inevitably was an essential issue to answer the question of which variables reliably predict functions of music listening and music-selection behavior in daily life. It has been shown that commonly used variable selection procedures, such as step-wise regression (including forward, backward, combined forward-backward), lead to overestimation of regression coefficients and to selection of false positive predictors (Chatfield, 1995; Derksen & Keselman, 1992; Steyerberg, Eijkemans, & Habbema, 1999). As the number of predictor variables included in a model, the likelihood increases to find relationships in sampled observations which are not present in the actual population (Babyak, 2004). The tendency of statistical models to mistakenly fit sample-specific noise is known as overfitting (Babyak, 2004; Hawkins, 2004). Overfitted models are not going to produce reliable predictions of unseen data as they contain associations that are only present in the sample used to build the models but not in the general population of interest. These problems might be one of the factors underlying the replication crisis in psychology (Open Science Collaboration, 2015), since many experimental studies in psychology cannot successfully be replicated. This problem is especially pronounced for findings within the field of social psychology (Open Science Collaboration, 2015). Yarkoni and Westfall (2017) therefore suggest "that an increased focus on prediction, rather than explanation, can ultimately lead us to greater understanding of behavior" (Yarkoni & Westfall, 2017, p. 1). In their paper, they argue for a shift from explanatory modeling (i.e., focusing on model fit indices like R^2 while building statistical models) to predictive modelling (i.e., focus on the prediction of unseen data). The field of statistical learning has developed several techniques and methods to optimize models for the prediction of unseen data and to minimize overfitting (Gareth, Witten, Hastie, & Tibshirani, 2015), and several of those methods can be used for variable selection. While some techniques, such as random forest or support vector machines, have been shown to produce accurate predictions, interpretation of model coefficients are difficult (Breiman, 2001; Gareth et al., 2015; Vapnik, 1999). If researchers aim to interpret model coefficients, the least absolute shrinkage and selection operator (Lasso), originally proposed by Tibshirani (1996), has become a prominent tool for variable selection in several scientific disciplines (e.g., medicine, bioinformatics, econometrics). Lasso is a shrinkage or penalization method that is also applicable in the context of linear regression. Ordinary least squares regression parameters (β_0, β_1,…, β_p) are estimated by minimizing the residual sums of squares (RSS) given by

$$RSS = \sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j\, x_{ij})^2 \tag{2.9}$$

where n denotes the number of observations and p denotes number of included predictor variables. The Lasso coefficients, $\hat{\beta}_\lambda^L$, minimize the quantity

$$\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j\, x_{ij})^2 + \lambda\sum_{j=1}^{p}|\beta_j| \tag{2.10}$$

which can also be written as

$$RSS + \lambda\sum_{j=1}^{p}|\beta_j| \tag{2.11}$$

where λ is a tuning parameter controlling the amount of shrinkage (also called L1 penalty) that is dependent on the number of predictor variables included. When λ is zero, Equation 2.11 equals the RSS, and the resulting coefficients will be identical to ordinary least square regression coefficients. With growing λ, some of the regression coefficients will be set to zero, which is why it can be used for variable selection. Very large values of λ will set all coefficients to zero. Hence, selecting an optimal value for λ is critical. In practice, the value of λ is chosen using *K*-fold cross-validation, a technique of randomly splitting the data into *K* folds of approximately equal size (Gareth et al., 2015). Then, *K*-1 folds are used as a training set to estimate a Lasso regression, while the remaining fold (validation set) is used to calculate the mean squared error (MSE), which in the regression setting is given by

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2.12}$$

Where $\hat{y}_i$ denotes the prediction of the ith observation and n is the number of observations. This procedure is repeated *K* times, and each time another fold is used as a validation set. This results in *K* estimates of the test error, MSE_1, MSE_2,…, MSE_K. The *K*-fold cross validation error is computed by averaging these values:

$$CV_{(K)} = \frac{1}{K}\sum_{k=1}^{K} MSE_k \tag{2.13}$$

For the selection of the optimal tuning parameter λ_{opt}, a number series (grid) of λ values is used. The grid should cover a range from zero to a value of λ for which all coefficients are set to zero (λ_{max}). For each of the grid values, the *K*-fold cross-validation error is computed. Then, the λ value for which the *K*-fold cross-validation error was smallest is selected as λ_{opt}. Finally, the Lasso regression is re-estimated using all available observations and the previously selected value of λ_{opt}. Using cross-validation for the selection of λ_{opt} simultaneously optimizes the Lasso regression model for the prediction of unseen data.

While the Lasso overcomes most of the problems discussed in the beginning of this section, it possesses limitations. Recent research has shown that the selection of λ_{opt} is extremely sensitive to the fold assignment of the cross-validation procedure (Krstajic, Buturovic, Leahy, & Thomas, 2014). Thus, depending on the random assignment of the data into *K* folds, λ_{opt} can differ substantially, resulting in varying amounts of included predictor variables in the final model. In addition, the selection of λ_{opt} based on cross-validation tends to select too many variables that are not associated with the outcome variable (Hesterberg, Choi, Meier, & Fraley, 2008; Meinshausen, 2007). To overcome these limitations, Roberts and Nowak (2014) introduced the percentile-Lasso, which is a modification of the standard-Lasso using repeated cross-validation instead of a single cross-validation cycle. In particular, the percentile-Lasso computes the *K*-fold cross-validation error for each of the repetitions, using a unique random fold assignment for each cycle. This produces a set of optimal λ values from which the final λ_{opt} is selected by calculating the θ-percentile of this set. Roberts and Nowak (2014) showed that in most circumstances, $\theta = 0.95$ produces good and reliable results (i.e., selecting fewer noise variables and reliably including the correct variables).

To date, in music psychology few attempts have been made to overcome the problems of overfitting, and statistical learning procedures are used very sparsely. In particular, research on music listening in everyday life has had to deal with numerous variables (e.g., Krause, North, & Hewitt, 2014; Randall & Rickard, 2017), but none of the recent approaches address these collateral problems. Hence, the present dissertation focused on minimizing overfitting and optimizing models for the prediction of unseen data by employing the percentile-Lasso.

3 Empirical Investigations

3.1 Paper 1: Personal and situational influences on the functions of music listening

The following chapter has already been published as a paper in the peer-reviewed journal *Psychology of Music* (Sage Publications).

> Greb, F., Schlotz, W., & Steffens, J. (2017). Personal and situational influences on the functions of music listening. Psychology of Music. Advance online publication. doi:10.1177/0305735617724883

The paper was written together with Wolff Schlotz (Max Planck Institute for Empirical Aesthetics) and Jochen Steffens (Technische Universität Berlin, Fachgebiet Audiokommunikation). The text is presented here in its original wording as it was published in the journal (Postprint), so that some repetitions of the introduction above in the paper were inevitable. In order to achieve a consistent typographic style throughout the whole dissertation minor modifications have been necessary (e.g., changes to positions and formats of figures and tables).

Personal and situational influences on the functions of music listening

3.1.1 Introduction

The functions of listening to music are manifold, and speculation about the effects of music dates back to antiquity (Barker, 1989). Music has become virtually omnipresent in the Western world, in particular due to the development of portable music players, loudspeakers, and the distribution of smartphones with integrated music playback systems. As a result, music listening now represents one of the most common leisure activities (Reinhardt, 2015). The constant availability of music has significantly changed the ways people listen to music (Hargreaves & North, 1999). Before the invention of recording and broadcasting techniques around 1900, people could listen to music only when it was performed live; they therefore either had to attend events where music was played (for instance during concerts devoted directly to music listening, in taverns, at social or religious gatherings, etc.) or had to perform it themselves. In contrast, people today listen to music in all kinds of circumstances and locations: in transit, while engaged in sports or exercise, while doing housework, and so forth (North, Hargreaves, & Hargreaves, 2004). Having the possibility to listen to music in such diverse situations enables people to actively and individually engage with music by choosing music that fulfills specific functions in certain situations (see, e.g., DeNora, 2000; Heye & Lamont, 2010). Research has identified a vast number of functions that music listening can fulfill (for an overview, see Schäfer, Sedlmeier, Städtler, & Huron, 2013). Interestingly, the majority of research on the functions of music listening has focused on the associations between individual differences and the ways in which people interact with music. Few studies have investigated the potential influence of the concrete situation (i.e., time-varying influences) on music listening behavior. In addition, studies have either focused on individual differences or on situational influences, but in reality people interact with the situation in which they reside. Therefore, the influences of both aspects – person-related and situational variables – need to be studied to explain real-life music listening. There is still not enough empirical evidence to formulate a theory that would explain the complex interactions that take place when people listen to music in everyday life (Sloboda & Juslin, 2010; von Georgi, Grant, von Georgi, & Gebhardt, 2006). The present study therefore attempts to provide relevant new evidence for such a theory by investigating the relative impact of individual differences and situational influences on the functions of music listening. The findings are expected to deliver empirical evidence that might guide future theory development and help explain who listens to what kind of music, in which situation, and why.

3.1.1.1 Individual differences and the functions of music listening

The *functionality* of music listening refers to the intentional use of music to accomplish specific goals in specific situations, such as eliciting personal memories, getting energized, or making time go by more quickly. Research that focuses on individual differences associated with the functions of music listening has mainly investigated the relationships between music listening and factors such as age, gender, personality traits, health, well-being, and musical taste. In addition, typology research has tried to cluster people according to the ways in which they engage with music – based on the assumption that listeners consistently try to achieve the same goals by listening to music – whereas cross-cultural studies have focused on cultural differences related to the functions of music listening. In the following, we discuss findings of empirical studies based on these approaches in more detail.

Research on gender differences has consistently shown that women tend to use music for affective functions (e.g., expressing feelings and emotions), coping, and enhancement (Boer et al., 2012; Chamorro-Premuzic, Swami, & Cermakova, 2012; Kuntsche, Le Mevel, & Berson, 2016; North, 2010), while men tend to use music for cognitive or intellectual reasons (Chamorro-Premuzic et al., 2012). Some studies have found evidence for additional differences. Boer et al. (2012) showed that females also tend to use music for dancing and to express cultural identity, and Kuntsche et al. (2016) found that girls listen to music more frequently for social motives than boys. According to North (2010), women are more likely than men to report listening to their favorite music style for enjoyment, to relieve boredom, to relieve tension, and to reduce loneliness. In contrast, men tend to use their favorite music to be creative and use their imagination, to create a mental image for themselves, and to please friends (North, 2010).

The findings are rather diverse when it comes to the effects of age on the functions of music listening. Lonsdale and North (2011) showed that participants beyond adolescence and early adulthood are less likely to use music to regulate their emotions, participants over 30 are less likely to reminisce about the past through music, and participants over 50 less frequently report using music for social functions. Chamorro-Premuzic et al. (2012) and North (2010) found negative associations between age and diverse functions of music listening and the amount of music consumption. This is in line with several findings that show that the subjective importance of music increases until the mid-20s and then decreases again (for an overview, see Dollase, 1997). In contrast, Laukka (2007) found an increase of subjective importance of music with age in participants of higher age. He also showed that the elderly (aged 65–75 years) use music to experience emotions and to relax.

A number of studies found associations between personality traits and functions of listening to music. Openness to experience was found to be associated with cognitive and intellectually-stimulating functions of music listening, and neuroticism with affect-regulating functions (i.e., regulating moods and emotions; Chamorro-Premuzic & Furnham, 2007; Chamorro-Premuzic, Gomà-i-Freixanet, Furnham, & Muro, 2009; Chamorro-Premuzic et al., 2012; Chamorro- Premuzic, Swami, Furnham, & Maakip, 2009; Vella & Mills, 2017; von Georgi & Hock, 2015). Moreover, Chamorro-Premuzic and Furnham (2007) showed that intelligent and intellectually-engaged people are likely to listen to music for cognitive stimulation, and that introverted people tend to use music for affect regulation.

Research investigating the relationships between the functions of music listening and musical tastes or musical preferences has consistently shown strong associations between the strength of music preference and diverse functions of music listening (Schäfer, 2016; Schäfer & Sedlmeier, 2009; Schäfer & Sedlmeier, 2010). The communicative functions of music listening (e.g., expressing identity/values) were shown to have the strongest associations with the intensity of a participant’s preference for their favorite music (Schäfer & Sedlmeier, 2009; Schäfer & Sedlmeier, 2010). These findings are in line with those of Chamorro-Premuzic et al. (2012), who demonstrated positive associations between the functions of music listening and music consumption, such as buying music or attending concerts. In addition, Schäfer and Sedlmeier (2009) found varying correlations between liking a music style and several functions of music listening, showing that fans of different music styles like their music due to certain functions of music listening (e.g., fans of rock music and of rap music reported liking their music because it expresses their identity). These findings are in line with those of von Georgi et al. (2006) and Getz, Chamorro-Premuzic, Roy, and Devroop (2012) who also found correlations between specific functions of music listening and liking certain music styles.

A number of studies found inconsistent associations between cultural factors and the functions of music listening. Some functions were found to have stronger cultural associations (e.g., sociocultural functions such as expressing cultural identity) than others (e.g., social bonding, dancing; Boer et al., 2012; Boer & Fischer, 2012). In contrast to these findings, several studies did not find any major differences when comparing different cultures; for example, there is no difference between English and American adolescents (Tarrant, North, & Hargreaves, 2000), Germans and Indians (Schäfer, Tipandjan, & Sedlmeier, 2012), and Pakistanis and the English (Rana & North, 2007). It is interesting to see that the relationships between neuroticism and the use of affect-regulating functions of music, and the relationships between openness to experience and the tendency to use cognitively stimulating functions of music listening seem to be stable across different cultures (Chamorro-Premuzic, Gomà-i-Freixanet, et al., 2009; Chamorro-Premuzic, Swami, et al., 2009). In sum, these findings provide support for the assumption that some cross-cultural universalities and certain cultural specificities exist in the functions of music listening.

Mental health and well-being were also found to affect the functional use of music. A number of studies have demonstrated that people with poor mental health (e.g., people suffering from depression or negative affectivity) or well-being (e.g., life satisfaction) tend to listen to music for its coping or affect-regulating functions (Getz et al., 2012; Kuntsche et al., 2016; Laukka, 2007; North, 2010; Randall & Rickard, 2016; Randall, Rickard, & Vella-Brodrick, 2014; Vella & Mills, 2017; von Georgi et al., 2006).

We are not aware of any studies that specifically investigated the associations between musical training and the functions of music listening, although Lehmann (1993) did find differences between the functions of music listening for musicians and for non-musicians. We therefore infer that musical training influences the ways people engage with music.

The field of typology research has tried to cluster listeners into groups according to the ways they listen to or engage with music (see, e.g., Adorno, 1975; Behne, 1986; ter Bogt, Mulder Juul, Raaijmakers, Quinten, & Gabhainn, 2011). Approaches within this research field either construct the listener groups theoretically (e.g., Adorno, 1975) or empirically (e.g., Behne, 1986; ter Bogt et al., 2011). All these approaches have followed the basic assumption that a person is a certain kind of listener, meaning that people always listen to music in the same way or use music listening for the same functions.

In sum, people differ in the ways in which they engage with music, and these differences can to a certain extent be attributed to several of the listener's individual characteristics.

3.1.1.2 Situational influences on the functions of music listening

Music listening always takes place in a triangulation between the listener, the situation, and the music. Although no music researcher is likely to disagree with this statement, the amount of literature investigating the situational (i.e., time-varying) influences on the functions of music listening is still quite small, and the ways in which people interact with music in specific situations still require further examination. Nevertheless, the few studies that have investigated such situational influences have already revealed a significant set of findings, which will be discussed in the following.

One question that immediately comes to the fore when we think about music listening in a specific situation is about *where* this listening is taking place. Studies that tackle this question have consistently found that nowadays, music listening takes place predominantly at home, while driving, or while using public transport (Greasley & Lamont, 2011; Krause, North, & Hewitt, 2014b; North et al., 2004). With regard to the influence of location on the functions of music listening, North et al. (2004) showed that the frequency of specific functions of music listening varies across different locations, and certain functions were predominately reported while being in a particular locality ("creating the right atmosphere", for instance, was most often reported when being in a night club or pub). In line with these findings, Krause et al. (2014b) found that the intensity of the consequences of listening to music varies across listening locations (e.g., music in the gym was experienced as more motivating than music in a restaurant).

Research has furthermore shown that another important situational characteristic is the core activity that is performed while listening to music. Research consistently found that music listening mostly occurs during personal maintenance (e.g., housework, cooking), active leisure activities (e.g., exercise, socializing), and travel (e.g., driving, walking), while music listening that is not accompanied by any other activity is relatively uncommon (Greasley & Lamont, 2011; Juslin, Liljeström, Västfjäll, Barradas, & Silva, 2008; North et al., 2004; Sloboda, O'Neill, & Ivaldi, 2001). Greasley and Lamont (2011) highlighted the great individual variability of activities people engage in while listening to music. Whereas some participants reported never listening to music while working, others reported that they could not work without music. With reference to the question of how the activity performed while listening is related to the functions of music listening, Heye and Lamont (2010) found that people who frequently listen to music while on the move mainly listen for the functions of enjoyment, passing time, and enhancing emotional states. Kamalzadeh, Baur, and Möller (2012) showed that several music listening variables (such as changing moods) are affected by the activity that accompanies the music listening. Even though these studies did not specifically investigate the functions of music listening, their findings support the notion that activities performed while listening to music are specifically associated with certain functions of music listening.

Moreover, the presence of other people plays a crucial role in the characterization of a listening situation. Various studies have shown that people mostly listen to music either alone or with friends (Greasley & Lamont, 2011; Juslin et al., 2008; North et al., 2004; Rana & North, 2007; Tarrant et al., 2000). However, Greasley and Lamont (2011) pointed out that the amount of solitary music listening varies considerably between individuals. Two studies that specifically delved into the influence that social contexts exert on functions of music listening revealed significant effects of the presence of others on the observed frequency of a broad set of functions (such as "helping to concentrate", "helping to pass time", "bringing back certain memories"; North et al., 2004; Rana & North, 2007). Additionally, Tarrant et al. (2000) showed that people who mainly listen to music while they are alone are also more likely to use music for the fulfillment of emotional needs. The findings with regard to the emotional effects of music when listening together with others have been inconsistent. While Liljestrom, Juslin, and Västfjäll (2012) found more intense emotional responses to music when people listened together with a close friend or partner, Egermann et al. (2011) observed more intense responses when people listened to music alone. To sum up, there is evidence that the presence of others has an effect on the functions of music listening, but the specific relationships between social context and these functions still require further exploration.

The level of choice that one has also constitutes a fundamental influence on the functions of music listening. The concept of level of choice can refer either to the fundamental fact that people have the possibility to choose the music they listen to, or to the different ways people select the specific music they are listening to (selecting a certain piece, enabling shuffle mode, etc.). Heye and Lamont (2010) demonstrated that mobile listeners who mainly use the shuffle mode predominantly use music to help them pass the time. In contrast, specific choosers tend to use music for enjoyment or to create or accentuate emotions. Greasley and Lamont (2011) found higher levels of choice to be associated with certain functions of music listening (i.e., enjoyment, relaxation, help to concentrate/think). Krause, North, and Hewitt (2014a) showed that for people who do not have any control over what they listen to, music is unlikely to fulfill purposive (e.g., "helped me concentrate") or actively engaged functions (e.g., "helped me pass the time"). In addition, Krause, North, and Hewitt (2015) found that recorded broadcasted music is associated with feeling lethargic, while personally-chosen music promotes contentment. These findings support the notion that a higher level of choice is associated with a higher level of beneficial functions of music listening.

Yet another variable that has been shown to affect the functions of music listening is the music's mode of presentation. This variable on the one hand differentiates between music presented live or played back, and on the other hand distinguishes between the devices used to play music (e.g., CD player, smartphone). Research consistently showed that whereas listening to recorded music is the dominant mode of how people listen to music today, listening to live music has become a rather uncommon event (Greasley & Lamont, 2011; Krause et al., 2015). Moreover, Krause et al. (2015) revealed that the mode of presentation can affect the perceived consequences of music listening in a variety of ways. They demonstrated that devices that rely on controlled listener input (MP3 players, smartphones and the like) are associated with purposive and actively engaged consequences of listening to music (such as helping to concentrate or learning about the music), while validation-seeking consequences (e.g., making oneself look good) were associated with live music performed in public. This suggests that functions of music listening might also be dependent on the mode of presentation. It is also important to note here that the mode of presentation is strongly related to the listener's level of choice. Listening to the radio has a lower level of choice compared to listening using an MP3 player (Krause et al., 2014a).

When investigating the situational variability of the functions of music listening, one must also consider the momentary mood of a listener. The most common functions of music listening related to initial mood are those concerned with affect regulation. There are several coexisting, partially opposing approaches to the affect-regulating functions of music listening. The most prominent among these are Katz and Foulkes's (1962) "uses and gratification" approach, Berlyne's (1971) arousal theory, Zillmann's (1988) mood management theory, and North and Hargreaves's (2000) arousal state-goal approach. Affect regulation is only one of the many functions of music listening. Since this paper has a broad focus on the entirety of music listening functions, we will here report just a small selection of the findings. Konečni – following Berlyne's arousal-based approach – conducted several studies demonstrating that people select music to moderate their arousal to an optimal level (for an overview, see Konečni, 1982). These findings were elaborated upon by North and Hargreaves (2000), who demonstrated that people select music to reach certain arousal state goals (e.g., choosing arousing music to get energized during exercise). The momentary mood the listener experiences when choosing what music they want to listen to can therefore be said to influence the affect-regulating functions of music listening.

Another factor that bears on the functions of music listening is the time of day when music listening occurs. Several studies on the influence of time of day on music listening behavior found significant associations. North et al. (2004) showed that music is more likely to be used to help pass the time during the workday (8:00 a.m. – 4:59 p.m.) than during the evening (5:00 – 11:00 p.m.). Rana and North (2007) found that their participants were more likely to use music to help them concentrate or think during the workday than during the evening. Furthermore, Krause et al. (2014b) revealed several interaction effects of the time of day on the perceived consequences of listening to music. Specifically, they demonstrated that actively engaged listening (e.g., "learning about the music", "bringing back memories") is experienced differently depending on the time of day when music is heard in public places or on weekends. One must therefore also consider the time of day when investigating the situational variance of the functions of music listening.

Most of the above studies focused on the effects of a single variable on the functions of music listening. To briefly reiterate, the main variables are: gender, age, personality traits, musical taste, strength of music preference, cultural differences, mental health, psychological wellbeing, musical training, listening location, main activity while listening to music, presence of others, level of choice, mode of presentation, momentary mood, and time of day. However, the relative impact of variables in the context of other relevant variables has not been sufficiently examined. This is particularly important considering that real-life situations involve all of the aforementioned factors as simultaneous influences on the subjective goals and functions of listening to music.

3.1.1.3 Aim of the present study

The aim of our study was to investigate the relative impact of individual (i.e., constant) and situational (i.e., time-variant) influences on a broad range of functions of music listening. We were also interested in identifying the most important variables that predict the functions of music listening in the context of other relevant variables. Therefore, we aimed at integrating a broad set of potentially relevant variables that influence music listening functions as identified by previous research into a comprehensive model.

To address these topics, we conducted an online study asking participants to sequentially describe three self-chosen listening situations. This approach was inspired by North and Hargreaves (1996), who asked their participants to imagine a specific situation that was selected by the experimenters. As we were interested in situations that actually occur in the daily lives of our participants, we decided to give them the freedom to choose the situations themselves. For each listening situation, participants answered several questions related to the situation and the functions of music listening in that situation. We also measured multiple variables pertaining to participant characteristics (e.g., personality, musical taste). All variables were entered into a hierarchical linear regression model to estimate their impact on functions of music listening. We expected to replicate established findings on both the situational and the person-related variables. We furthermore expected to reveal novel associations that had not been found by any previous study.

As prior studies have not investigated the relative impact of the two levels of influences (personal and situational) on functions of music listening, we were particularly interested in answering the following questions:

- Are different functions of music listening similarly influenced by individual and by situational factors, or are there considerable variations? If the level of influence varies, to what extent does it vary between the diverse functions?
- Which are the key variables predicting the functions of music listening on the person and situation levels?

3.1.2 Methods

3.1.2.1 Sample

The study was advertised via mailing lists from German universities, posters displayed at the Goethe University Frankfurt, and on Facebook. As an incentive, respondents could enter a lottery to win a 15 Euro voucher for Amazon (chance of winning was 1 in 10).

In total, 945 people started the study. One hundred and seventy-six participants stopped during the description of the first situation, 133 while describing the second situation, and 9 while reporting the third situation. Forty respondents did not understand the instructions correctly and wrote down multiple situations in the first text field. All these participants (n = 358; 38% of those who started the study) were excluded from the analyses, which is an average exclusion and dropout rate when compared to other online studies (e.g., Egermann & McAdams, 2013; Egermann, Nagel, Altenmüller, & Kopiez, 2009). The remaining n = 587 participants (58% female) included in the study had a mean age of 25.4 years (SD = 7.0).

3.1.2.2 Design and measures

The questionnaire consisted of three sections: questions about the situation, questions about functions of music listening in the specific situation, and questions about personal information. Table 1 shows all situational variables that the study included.

Our objective was to capture a wide range of potential functions of music listening. Part of this enterprise was a reanalysis of data collected by Schäfer et al. (2013), who performed a literature review and compiled a large and comprehensive list of possible functions of music listening. They asked 834 participants to rate to what degree music listening fulfills these functions in any possible situation where music might be heard. A principal component analysis revealed three distinct dimensions of the functions of music listening. To obtain the most diverse set of different functions and to disclose hierarchically-underlying sub-factors, we performed separate principal component analyses for each of the three main dimensions using the data provided by Schäfer et al. (2013). The analysis yielded 24 properly-interpretable subfactors and we selected one item per sub-factor. We furthermore omitted two sub-factors on the basis of low prevalence of the respective items (namely, spirituality and express political attitude). This resulted in 22 items that we phrased in such a way that they could vary across situations (see Table 2; for details see Steffens, Greb, & Schlotz, 2016). Participants answered the items ("*I listen to music because …*") on a 7-point rating scale for each situation (1 = *Not at all* to 7 = *Completely*). As previous research showed that each listening experience involves several functions (e.g., Greasley & Lamont, 2011), we decided to measure all 22 functions for each situation.

In addition, we collected the following person-related information: gender; age; Big Five personality traits using the BFI-10 (Rammstedt, Kemper, Klein, Beierlein, & Kovaleva, 2013); intensity of music preference measured by a 6-item inventory (Schäfer & Sedlmeier, 2009); musical training using the third scale of the Gold-MSI, consisting of 7 items (Schaal, Bauer, & Müllensiefen, 2014); and musical taste using an inventory currently under construction at the Max Planck Institute for Empirical Aesthetics. This unpublished musical taste inventory assesses an individual's liking for a broad variety of musical styles (19 in total) using liking ratings on a 7-point scale (1 = *Don't like at all* to 7 = *Like very much*). Participants could also indicate not being familiar with a certain style of music. No liking ratings were measured for these styles. Details on the styles that were assessed and on the factorial structure of the inventory are provided in the Results section below.

Table 1. Situational characteristics measured in the online study.

Item	Response options
Situation description:	Free response format
Are there other persons present?	Single forced choice: Alone Others present & no interaction Others present & interaction + Option: Nonspecific[a]
Do you have the chance to choose the music?	Single forced choice[b]: Yes Radio Disco Concert No + Option: Nonspecific[a]
Where does this situation typically take place?	Free response format + Option: Nonspecific[a]
How is your mood at the time you decide to listen to music?	Valence: good – bad; Arousal tired – awake; 7-point scale + Option: Nonspecific[a]
How important is your mood for your decision to listen to music?	not important at all – very important; 7-point scale
At which time of day does this situation usually occur?	Multiple choice: Early morning Morning Noon Afternoon Evening Night
How much attention do you pay to the music in this situation?	little – a lot; 7-point scale + Option: Nonspecific[a]
How often does the situation just described occur in your everyday life?	Single forced choice: 1-4 times per year 5-11 times per year 1-3 times per month 1-3 times per week 4-7 times per week more than once per day

Note. Instruction: Please describe the first/ second/ third situation in which you typically listen to music in a concise sentence giving as much details as necessary. Afterwards please answer the following questions with regard to the outlined situation. These items were presented for each of the three situations described by a participant. All items were presented in German language (available upon request).

[a]'Nonspecific' indicates that the situation reported could not be described by the specific item. [b]'Yes' indicates full freedom of choice; 'Radio', 'Disco' and 'Concert' indicate actively involved possibilities to choose the music with limited freedom of choice (e.g., choosing a radio station); 'No' indicates no freedom of choice (e.g. listening to music at the supermarket).

Table 2. Twenty-two functions of music listening

Why do you listen to music in the situation you just described?
I listen to music because…
it helps me learn about myself.
it gives me intellectual stimulation.
it reduces my stress.
it makes me feel less lonely.
it puts fantastic images or stories in my head.
it lets me forget the world around me.
it mirrors my feelings and moods.
it gives me a way to let off steam.
it reminds me of certain periods of my life or past experiences.
it gives me goose bumps.
it addresses my sense of aesthetics.
it helps me understand the world better.
it makes me feel connected to all people who like the same kind of music.
I am interested in the musicians or bands.
I want to inform myself about hits and trends.
I can learn about new pieces.
it enables me to kill time.
it enhances my mood.
it makes me feel fitter.
I can move to the music.
I need it in the background while I do other things.
I can sing or hum along.

Note. All items were presented for each of the three situations described by a participant. Items were measured using a 7-point scale (1 = *Not at all* and 7 = *Completely*). All items were presented in German language (available upon request).

3.1.2.3 Procedure

Data were collected online (browser-based) through Unipark/EFS Survey software (Questback GmbH). Participants were redirected to the online survey after clicking a participation link in an email or scanning a QR Code on a poster. On the landing page, they were informed about the general procedure and the focus of the study, the voluntary nature of their participation, the possibility to terminate the survey at any time, and the opportunity to take part in a lottery to win a voucher. They were then asked to sequentially describe three self-selected situations in which they typically listen to music. First, the participants were asked to describe the situation they chose in a concise sentence, in as much detail as they considered necessary. Then, the participants answered questions regarding this situation and functions of music listening in that specific situation (Tables 1 and 2). This procedure was repeated for each of the three situations. After describing the three listening situations, participants reported on person-level variables. Finally, they could provide their email address to take part in the lottery for Amazon vouchers.

3.1.2.4 Data analysis

A principal component analysis was computed to reduce the number of independent variables related to musical taste. Varimax rotation was applied in order to obtain distinct and uncorrelated factors and to get results comparable to those of Rentfrow, Goldberg, and Levitin (2011), who also applied this kind of factor rotation in their analysis. As the musical taste questionnaire included the possibility to choose “I don’t know” for a music style, we used imputation to replace missing data. More specifically, we replaced the missing data points with the mean value of the ratings of the respective music style.

Another aim of the pre-analysis was to reduce the number of dependent variables and to reveal underlying broader constructs of functions of music listening. All 22 items that measured functions of music listening were therefore entered into a complex exploratory factor analysis for ordered categorical factor indicators (seven categories) with robust weighted least square estimation (WLSMV), and a robust sandwich estimator to account for the cluster-structure of observations within individuals, and Geomin rotation using Mplus v7.3 (Muthén & Muthén, 1998–2012).

Descriptions of the individual music listening situations were given in free response format. After a comprehensive review of all descriptions, 11 activity categories were defined. A research assistant not involved in the development of activity categories then classified each description into one of these categories. Finally, these classifications were double checked by two researchers based on a randomly chosen small subsample. Table 3 presents the category labels, descriptions, and relative frequencies.

Table 3. Explanation and descriptive statistics of the 11 coded activities

Activity while listening	Description	% of total activities
Being on the move	Situations in which the main activity was being on the move (e.g. by car, subway, or bike).	28.4
Housework	Situations in which the main activity was doing any kind of housework (e.g. washing up, cleaning, getting ready).	15.0
Working & studying	Situations in which the main activity was working, learning, or studying.	13.3
Others	Situations which could not be coded to one of the other categories.	12.1
Pure music listening	Situations in which the main activity was listening to music only.	7.3
Party	Situations in which the main activity was celebrating or dancing in a club or disco (dancing which was mentioned in a training context was coded as Exercise).	6.8
Relaxing & falling asleep	Situations in which the main activity was relaxing, getting new energy, or trying to fall asleep.	6.5
Exercise	Situations in which the main activity was exercising or doing sports.	5.8
Coping with emotions	Situations in which the main activity was coping with own emotions.	2.2
Making music	Situations in which the main activity was playing or making music.	1.3
Social activity	Situation in which the main activity was interacting with others (e.g. cooking and eating with friends, or playing with friends).	1.2

Note. Each situation described in free response format (N = 1,761) was classified into one activity category.

Free responses on listening location were classified by a research assistant to one of seven location categories (at home, workplace, transportation vehicle, music event location, public space, sports facility, others). Due to high correlations between activity and location categories, we excluded listening location from the analysis to avoid multicollinearity. We decided to include activity in the analysis as this variable captured more detailed information compared to listening location.

Measurements of the situation and the functions of music listening were taken three times per person, resulting in data with a two-level structure: measures (situations) nested within individuals. Multilevel linear regression models were therefore formulated to estimate the impact of personal and situational variables on the factor scores of functions of music listening. This data analysis approach allows for the inclusion of time-varying (i.e., situation-specific) predictors and the analysis of unbalanced designs, while simultaneously accounting for non-independence of observations within subjects. An intercept-only model was initially calculated to differentiate between variance components at the two levels. Categorical variables were included as dummy variables (coded as 0, 1). All situational variables were transformed by centering them around the within-person mean. This calculation produced within-subject (W-S) predictors that varied within, but not between individuals. In addition, all mean values of the situational variables were added to the model to evaluate between-subject (B-S) effects of these variables. Thus, the W-S situational predictors in this model represent "pure" situational influences (e.g., situation-specific individual state of high arousal as a deviation from this individual's mean arousal states in all situations sampled for this person) and the B-S situational variables account for individual differences in situational variables (e.g., individual differences in mean arousal levels). As one of our aims was to identify the most important variables predicting functions of music listening, one model was formulated for each dependent variable containing all three sets of predictors (W-S situational predictors, B-S situational predictors, and B-S person-level predictors). This was done using the *lmer* function from the *lme4* package (Bates, Mächler, Bolker, & Walker, 2015) and the *step* function of the *lmerTest* package (Kuznetsova, Brockhoff, & Christensen, 2015), which performs automatic backward elimination of all effects in linear mixed-effect regression models within the development environment R-Studio (RStudio Team, 2015) of the software R 3.0.2 (R Core Team, 2015). The *step* function first performs backward elimination of the random part followed by backward elimination of the fixed part. *P*-values for the random effects were based on likelihood ratio tests, while *p*-values for fixed effects were based on *F*-tests using Satterthwaite's approximation. We used an alpha-level of $p < .01$ for random effects and $p < .05$ for fixed effects. This procedure was repeated until only significant predictors were left. As this procedure might result in a random effect being included in the model without its respective fixed effect, we manually included fixed effects regardless of their significance to specify significant random effects for which no fixed effect was included automatically.

As suggested by Nakagawa, Schielzeth, and O'Hara (2013), *marginal* and *conditional* R^2 values were computed as indices of explained variance. This was done using the *r.squaredGLMM* function of the *MuMIn* package (Barton, 2016). Whereas *marginal R^2 (R^2m)* indicates the proportion of variance explained by the fixed factor(s) alone, *conditional R^2 (R^2c)* indicates the proportion of variance explained by both fixed and random factors. As the effect sizes for the two B-S predictor sets (situation-related and person-related) could contain shared variance, and their sum was therefore likely to overestimate the amount of variance explained by B-S predictors, we also calculated R^2m for the two B-S predictor sets together.

To assess the importance of single predictor variables we calculated two indices, I_F and I_R, indicating consistency across functions and summative strength of associations. The first index, I_F, was a weighted index of variable consistency across musical functions (see Equation 1). I_F is a count indicator of how often a variable was included as a significant predictor in the five models, weighted by the number of items a variable was represented by (e.g., activity was represented by 10 items [i.e., dummy variables], attention was represented by one item [i.e., one continuous variable]) to achieve identical ranges for different predictor variables.

$$I_{Fi} = \frac{\sum_{k=1}^{m_i} S_{ik}}{m_i} \tag{1}$$

Where I_{Fi} is the weighted frequency index for variable *i*, m_i is the number of items which represented variable *i*, and S_{ik} the sum of significant associations of item *k* of variable *i* across all five models. For example, the sum of significant associations of all dummy coded activities (i.e., items) in all five models was divided by 10, as the variable activity was represented by 10 items. In contrast, for the variable attention (represented by one item), the sum was divided by one. Therefore, I_F scores range between 0 and 5 and provide a summary indicator of the consistency of each variable across musical functions. Low scores indicate specific associations between predictor and musical function factor scores, whereas high scores indicate consistent significant associations for a predictor across multiple musical function factor scores.

The second index, I_R, was based on explained variance of the predictors' fixed effects. We formulated a model containing only the significant predictors (i.e., items) representing a variable, calculated R^2m, and summed up this variable-specific R^2m values across all five models. Therefore, I_R scores theoretically could range between 0 and 5 (as the maximum amount of variance explained in a model is 1), and provide a summary indicator of the strength of association for each predictor variable across musical function factor scores. Low scores indicate weak associations (small amounts of variance explained), whereas high scores indicate strong associations between a variable and musical function factor scores across all functions. In accordance with the expectation that no single variable explains the complete variance in any model, I_R empirically varied between 0 and 0.43.

3.1.3 Results

3.1.3.1 Musical taste

A principal component analysis of musical taste suggested extraction of six factors with Eigenvalues greater than 1, and together accounted for 64.1% of variance in participants' ratings. We labeled the six factors with those two music styles that showed the highest loadings on each respective factor (see Table 4): *Blues & Jazz, Techno & EDM, Other Cultures & Latin, Volksmusik & Schlager, Pop*, and *Rock & Metal*. Factor scores representing musical taste were used as independent variables for all further analyses.

3.1.3.2 Dimensions of the functions of music listening

The factor analysis performed on the items that assessed functions of music listening resulted in a five-factor solution (Eigenvalues: 6.65; 2.76; 2.04; 1.49; 1.06) with acceptable model fit (χ^2 = 1034.8; *df* = 131; $p < .001$; root mean square error of approximation [RMSEA] = .063; 90% CI [.059, .066]; comparative fit index [CFI] = .94; Tucker-Lewis index [TLI] = .90), a satisfactory simple structure after Geomin rotation, and small to modest factor intercorrelations (see Table 5). The factors were labeled: *Intellectual Stimulation, Mind Wandering & Emotional Involvement, Motor Synchronization & Enhanced Well-Being, Updating One's Musical Knowledge*, and *Killing Time & Overcoming Loneliness* (see Table 5).

Intellectual Stimulation mainly comprises functions in the cognitive domain, ranging from intellectual stimulation and learning about oneself to addressing the individual's sense of aesthetics. The cross-loadings of the two items "learning about oneself" and "addressing one's sense of aesthetics" on the *Mind Wandering & Emotional Involvement* factor suggest that these two functions also have an affective component

Table 4. Varimax-rotated loadings for 19 music styles on six factors

Musical Styles	Factor: Blues & Jazz	Techno & EDM	Other cultures & Latin	Volksmusik & Schlager	Pop	Rock & Metal	h²
Blues	.80						.70
Jazz	.77						.67
Funk	.64						.53
Soul	.60						.60
Reggae	.54						.39
Techno		.84					.73
EDM		.83					.71
House		.79					.70
Rap/Hip-Hop	.	.44			.40		.49
Other cultures			.75				.61
Latin			.65				.62
World music			.61				.54
Classical			.58				.55
German “Volksmusik”				.82			.73
German “Schlager”				.80			.74
Country				.60			.57
Pop					.81		.72
Rock						.90	.85
Metal					-.43	.74	.74

Note. Factor loadings < |.40| omitted. N = *587*.

mainly represented by the second factor. The *Mind Wandering & Emotional Involvement* factor represents functions that are imaginative and have an affective aspect. The diverse functions that show the highest factor loadings on this factor might indicate that the use of music for mind wandering might be associated with higher emotional involvement. The cross-loading of the item “helps me understand the world better” might reflect a cognitive-affective facet of this item, and the cross-loading of the item “forget the world around me” indicates that this function might also be addressed by moving to music. *Motor Synchronization & Enhanced Well-Being* comprises functions that have an active motoric component (presumably associated with increased arousal) as well as several positive effects like “reducing stress” or “letting off steam”. The combination of items loading on this factor suggests that the use of music to enhance wellbeing might be associated with motoric activity. The cross-loading of the item “to let off steam” might indicate that this function might also

Table 5. Geomin-rotated loadings for the functions of music listening on five factors. Factor score correlations are shown on the bottom of the table.

Function	Factor: Intellectual Stimulation	Mind Wandering & Emotional Involvement	Motor Synchronization & Enhanced Well-being	Updating One's Musical Knowledge	Killing Time & Overcoming Loneliness	R^2
I listen to music because…						
it gives me intellectual stimulation.	.83					.73
it helps me learn about myself.	.52	.44				.64
it addresses my sense of aesthetics.	.51	.31				.49
I am interested in the musicians or bands.	.27	.25			.26	.33
it reminds me of certain periods of my life or past experiences.		.78				.61
it mirrors my feelings and moods.		.71				.71
it puts fantastic images or stories in my head.		.68			.25	.56
it gives me goose bumps.		.63				.58
it helps me understand the world better.	.45	.47				.62
it lets me forget the world around me.		.41	.31	-.29		.50
it makes me feel fitter.			.86			.64
I can move to the music.			.82	.47	-.36	.82
it enhances my mood.			.71			.63
it gives me a way to let off steam.		.29	.65			.62
I can sing or hum along.			.47	.31		.34
it reduces my stress.			.40	-.39		.52
I want to inform myself about hits and trends.				.63	.54	.65
I can learn about new pieces.	.35			.55	.36	.57
it makes me feel connected to all people who like the same kind of music.	.27	.28		.40		.41
it enables me to kill time.					.61	.42
I need it in the background while I do other things.		-.36	.30		.39	.36
it makes me feel less lonely.		.29			.34	.31
Factor correlations						
Intellectual Stimulation	1.00					
Mind Wandering & Emotional Involvement	.43	1.00				
Motor Synchronisation & Enhanced Well-being	.07	.41	1.00			
Updating One's Musical Knowledge	.03	-.05	-.08	1.00		
Killing Time & Overcoming Loneliness	.15	.14	.31	-.08	1.00	

Note. Loadings < |.25| omitted. $N = 1761$.

be achieved while using music for mind wandering. The functions that have the highest factor loadings on *Updating One's Musical Knowledge* cover satisfying one's curiosity but also include a social aspect of feeling connected to other people. Finally, the *Killing Time & Overcoming Loneliness* factor represents passive functions including coping with feelings of loneliness. All further analyses of functions of listening to music were based on factor scores.

3.1.3.3 Representativeness of situations

In order to evaluate representativeness of the situations described by participants, we asked for frequency of situation occurrence in daily life. In our sample, 92% of the situations were reported to occur at least one to three times a month, and 73% at least one to three times a week. This indicates that participants reported frequent day-to-day situations rather than rare and untypical music listening events. Although very rare situations were probably not covered reliably, the high daily life frequency of the situations that were reported suggests representativeness for common music listening situations participants typically experience in their daily life.

3.1.3.4 Variance components of functions of music listening

In the next step, intra-class correlation coefficients (ICC) were calculated using intercept-only models predicting the five factors representing functions of music listening. On average, 36% of the variance of the functions of music listening was due to between-person differences, while 64% of the variance was attributable to within-person differences between situations (see Table 6). The proportion of variance accounted for by between- and within-person differences varied across factors. For example, between-person differences accounted for 47% of the variance in *Intellectual Stimulation* but accounted for only 21% of the variance in the factor *Updating One's Musical Knowledge*. For all five factors, the variance attributable to within-person differences between situations was higher than the variance due to between-person differences.

Table 6. Intraclass correlation coefficients and explained variance for the five final models predicting functions of music listening.

				R^2m			
Factor	ICC	R^2m	R^2c	W-S situation	B-S situation	B-S person	B-S situation & B-S person
Intellectual Stimulation	.47	.32	.70	.09	.16	.15	.23
Mind Wandering & Emotional Involvement	.35	.42	.70	.20	.18	.12	.22
Motor Synchronization & Enhanced Well-being	.42	.36	.68	.12	.13	.16	.24
Updating One's Musical Knowledge	.21	.34	.61	.24	.09	.01	.10
Killing Time & Overcoming Loneliness	.36	.29	.67	.13	.07	.08	.15
Mean (*SD*)	.36 (.10)	.34 (.05)	.67 (.04)	.16 (.06)	.12 (.04)	.10 (.06)	.19 (.06)

Note. Marginal R^2 (R^2m) describes the proportion of variance explained by the fixed factor(s) alone, and conditional R^2 (R^2c) describes the proportion of variance explained by both the fixed and random factors (see text for details).

3.1.3.5 Predicting the functions of music listening

Tables 7 and 8 show the results of mixed-effects regression model fitting using the *step* function to reveal the most important individual and situational predictors of the functions of music listening in the context of the complete set of predictors for the five function factors. Table 7 includes estimations of W-S effects and random effects, and Table 8 contains all the B-S effects. Each function factor was modeled separately, resulting in five final models. These five models provide a detailed analysis of the associations between individual and situational variables and the functions of music listening as they occur in daily life. Due to the relatively high complexity of the models, we will report one of the models (*Intellectual Stimulation*) in more detail below and will describe the other four more concisely.

Intellectual stimulation. Activity was the most important predictor on the W-S situational level. If the major reported activity was pure music listening, making music, working and studying, or relaxing and falling asleep, there was a higher chance that a person would report using music for intellectual stimulation in that situation. If, however, the primary activity performed while listening to music was exercise or housework, participants were unlikely to report using music for intellectual stimulation. Furthermore, a significant random effect was found for “exercise”, which means that the association between exercising and getting intellectually stimulated by music significantly varies between individuals. More specifically, the association was more negative for 10% of the participants than the fixed effect suggests, while for 10% of the participants the association was less negative (and it was actually positive for several participants). Moreover, the presence of other people was found to be significantly associated with listening to music for intellectual stimulation. When a person reported listening to music while interacting with others, it was less likely for the music to be reported to fulfill intellectually stimulating functions. Having the possibility to choose the music was significantly associated with high scores on Intellectual Stimulation. Finally, the more attention a person reported to pay to the music while listening to it, the more intellectual stimulation was reported. This association varied between individuals (slope varying from -0.59 to 0.19) as indicated by the significant random effect of the attention item.

In addition, several B-S situational predictors were found to have significant effects on intellectual stimulation caused by music. Participants who on average (over the situations reported) reported to listen to music as a main activity more frequently than others tended to use music as a resource for intellectual stimulation. In contrast, individuals who reported that they were typically more frequently than others to be doing housework or exercising while listening to music, or listening to music while being on the move or coping with emotions, showed lower mean values regarding the intellectually-stimulating function of music. Furthermore, people who reported a higher importance of mood in their decision to listen to music and people who generally pay more attention to music than others had higher average scores on intellectual stimulation by music. Participants who reported that they relatively often experienced situations in which they could not choose the music themselves also had lower factor scores on *Intellectual Stimulation*.

Finally, on the B-S personal level, a higher intensity of music preference was associated with high scores on *Intellectual Stimulation*, and participants scoring high on extraversion showed lower factor scores for *Intellectual Stimulation*. Lastly, participants with high liking ratings for the musical taste factors *Blues & Jazz* and

Table 7. Multilevel estimations for fixed effects on within subject level and random effects at person level predicting the five function factors.

Predictor variables	Estimate (*SE*)				
	Intellectual Stimulation[a]	Mind Wandering & Emotional Involvement[b]	Motor Synchronization & Enhanced Well-being[c]	Updating Ones Musical Knowledge[d]	Killing Time & Overcoming Loneliness[e]
Activity					
Being on the move				-0.25 (0.05)***	0.27 (0.04)***
Housework	-0.17 (0.05)***	-0.24 (0.05)***	0.34 (0.06)***	[f] 0.12 (0,07)	
Working & studying	0.39 (0.06)***	-0.27 (0.06)***	-0.17 (0.06)**	-0.53 (0.06)***	
Pure music listening	0.61 (0.08)***		[f] -0.17 (0.09)		
Party			0.21 (0.08)*		-0.41 (0.07)***
Relaxing & falling asleep	0.24 (0.07)***		-0.33 (0.08)***	-0.43 (0.08)***	
Exercise	-0.36 (0.09)***	-0.31 (0.07)***	0.67 (0.08)***		-0.48 (0.08)***
Coping with emotions		0.25 (0.11)*	[f] -0.23 (0.22)	-0.61 (0.13)***	-0.49 (0.11)***
Making music	0.89 (0.16)***	0.72 (0.16)***		-0.61 (0.17)***	
Social activity					
Presence of others					
Alone			0.10 (0.04)*	-0.27 (0.05)***	0.20 (0.04)***
Others present & no interaction				-0.42 (0.06)***	0.17 (0.05)***
Others present & interaction	-0.20 (0.05)***	-0.20 (0.05)***			
Possibility of choice					
Yes	0.10 (0.05)*	0.38 (0.04)***		-0.49 (0.05)***	
No			-0.52 (0.10)***		
Radio			-0.23 (0.06)***		0.29 (0.05)***
Disco		0.27 (0.10)**			
Concert		0.50 (0.09)***			-0.37 (0.08)***
Valence	[f] -0.00 (0.02)				
Arousal			0.07 (0.01)***	0.05 (0.01)***	
Importance of mood		0.03 (0.01)**	0.03 (0.01)***		[f]-0.01 (0.01)
Degree of attention	0.06 (0.01)***	0.17 (0.01)***	0.09 (0.01)***		[f] 0.01 (0.01)

(continued)

Table 7. (Continued)

Predictor variables	Estimate (*SE*) Intellectual Stimulation[a]	Mind wandering & Emotional Involvement[b]	Motor Synchronization & Enhanced Well-being[c]	Updating Ones Musical Knowledge[d]	Killing Time & Overcoming Loneliness[e]
Time of day					
Early morning					0.13 (0.04)***
Morning			0.13 (0.04)**		
Noon					
Afternoon					0.10 (0.04)**
Evening				-0.10 (0.04)*	
Night		[f] 0.04 (0.04)		0.10 (0.04)*	
Random effects					
Person level					
Variance intercept	0.25***	0.21***	0.22***	0.17***	0.21***
Variance housework				0.15**	
Variance working & studying		0.19***			
Variance pure music listening			0.23***		
Variance exercise	0.24**				0.13*
Variance coping with emotions			0.99***		
Variance valence	0.01*				
Variance arousal			0.01***		
Variance importance of mood					0.01***
Variance degree of attention	0.01**				0.01***
Variance night		0.09*			

Note. *SE* = standard error.
[a]n= 1300 observations within 555 persons. [b]n= 1724 observations within 582 persons. [c]n = 1347 observations within 549 persons. [d]n= 1374 observations within 556 persons. [e]n= 1727 observations within 583 persons. [f]Fixed effect retained in model because of significant random effect
* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 8. Multilevel estimations for fixed effects on between-subject level predicting the five function factors

	Estimate (*SE*)				
Predictor variables	Intellectual Stimulation[a]	Mind Wandering & Emotional Involvement[b]	Motor Synchronization & Enhanced Well-being[c]	Updating Ones Musical Knowledge[d]	Killing Time & Overcoming Loneliness[e]
Fixed effects					
Activity					
Being on the move	-0.35 (0.15)*				0.48 (0.13)***
Housework	-0.48 (0.15)**		0.61 (0.14)***		0.31 (0.14)*
Working & studying		-0.32(0.14)*			0.38 (0.14)**
Pure music listening	0.49 (0.19)**			0.58 (0.16)***	
Party			0.86(0.19)***		
Relaxing & falling asleep		0.37 (0.17)*			
Exercise	-0.89 (0.21)***		1.15(0.20)***		
Coping with emotions	-0.62 (0.31)*				
Making music					
Social activity					
Presence of others					
Alone					
Others present & no interaction					
Others present & interaction				0.43 (0.11)***	
Possibility of choice					
Yes				-0.49(0.09)***	0.26 (0.11)*
No	-0.42 (0.20)*				
Radio					0.83 (0.15)***
Disco					
Concert					
Valence					
Arousal					
Importance of mood	0.05 (0.02)**	0.11 (0.01)***	0.10 (0.02)***		0.08(0.01)***
Degree of attention	0.09 (0.03)***	0.16 (0.02)***	0.05 (0.02)*		

(continued)

Table 8. (Continued)

Predictor variables	Estimate (*SE*) Intellectual Stimulation[a]	Mind Wandering & Emotional Involvement[b]	Motor Synchronization & Enhanced Well-being[c]	Updating Ones Musical Knowledge[d]	Killing Time & Overcoming Loneliness[e]
Time of day					
Early morning					
Morning					
Noon					
Afternoon			0.19 (0.09)*		
Evening		0.21 (0.09)*			0.25(0.09)**
Night				0.17(0.08)*	
Person-related predictors					
Intensity of music preference	0.15 (0.02)***	0.14 (0.02)***	0.15 (0.02)***		0.12 (0.02)***
Musical taste					
Blues & Jazz	0.07 (0.03)**				
Techno & EDM		0.06 (0.02)**	0.08 (0.03)***		0.05 (0.02)*
Other cultures & Latin	0.09 (0.03)***				
Volksmusik & Schlager					0.05 (0.02)*
Pop	-0.12 (0.03)***			0.09 (0.02)***	0.06 (0.02)*
Rock & Metal			0.09 (0.09)***	-0.05 (0.02)*	
Personality traits					
Openness to experience		0.09 (0.03)**			
Conscientiousness					
Extraversion	-0.05 (0.03)*	-0.06 (0.02)**			
Agreeableness					
Neuroticism			0.11 (0.03)***		0.06 (0.02)*
Age			-0.01 (0.00)***		-0.02 (0.00)***
Sex[f]		-0.14 (0.05)**	-0.26 (0.06)***		
Musical training					

Note. *SE* = standard error.
[a]n= 1300 observations within 555 persons. [b]n= 1724 observations within 582 persons. [c]n= 1347 observations within 549 persons. [d]n= 1374 observations within 556 persons.
[e]n= 1727 observations within 583 persons. [f]0 = *female;* 1 = *male*. * $p < .05$. ** $p < .01$. *** $p < .001$.

Other cultures & Latin tended to use music for intellectual stimulation whereas participants with high liking ratings for the *Pop* factor on average tended to use the intellectual stimulating functions of music listening less.

Mind wandering and emotional involvement. On the W-S situational level, 11 variables significantly predicted the outcome variable. Positive associations were found for the reported activities “coping with emotions” and “making music”, all actively involved possibilities to choose the music (Yes, Disco, Concert), the degree of attention payed to the music, and the importance of mood for the decision to listen to music. Negative associations were found for doing housework, exercising, working, and studying while listening to music. Participants who reported that, in a given situation, other people were present and that they interacted with them, reported lower levels of mind wandering or emotional involvement. The model furthermore included two significant random slopes for “working and studying” and “night”, which showed that the associations of these predictors with scores on Mind Wandering & Emotional Involvement varied significantly across participants.

On the B-S situational level, five variables were found to contribute significantly to the prediction of the outcome. Participants who frequently reported to relax and fall asleep while listening to music, or to listen to music in the evening, tended to exploit the mind wandering and emotional qualities of music. This also applied to participants who on average reported paying higher levels of attention to music, or for whom mood had a higher importance in the decision to listen to music. In contrast, people who frequently reported listening to music while working or studying showed lower mean scores on the *Mind Wandering & Emotional Involvement* factor. As for the B-S personal level, intensity of music preference was positively associated with the *Mind Wandering & Emotional Involvement* factor. Extraversion was negatively associated, whereas openness and liking ratings for the musical taste factor *Techno & EDM* were positively associated, with scores on this function factor. Lastly, it was found that women reported to make more use of the mind wandering and emotional involvement functions of music listening than men.

Motor synchronization and enhanced well-being. Twelve predictors were significant on the W-S level; five of these were activities. Listening to music while doing housework, exercising, or partying were positively associated with Motor Synchronization & Enhanced Well-being, whereas negative associations with this factor were found for “working and studying” and for “relaxing and falling asleep”. Furthermore, positive associations were shown for the presence of others, time of day, arousal, degree of attention, and importance of mood. Not having the possibility to choose the music or listening to the radio were also associated with lower levels of using music for motor synchronization or for enhancing one’s well-being.

On the B-S situational level, the model included six significant predictors: three activities (housework, exercise, and party), time of day (afternoon), the average level of attention that participants reported paying to music, and the average importance of mood for their decision to listen to music. All six predictors were positively associated with scores on this factor.

On the B-S personal level, intensity of music preference, neuroticism, and the musical taste factors Techno & EDM and Rock & Metal showed positive associations with factor scores. Lastly, an age effect was included that showed that older participants on average had lower levels of listening to music for motor synchronization or enhancing one’s well-being. In addition, men reported lower levels than women.

Updating one’s musical knowledge. On the W-S level, all statistically significant activities were negatively associated with the reported use of music to update one’s musical knowledge. More specifically, lower levels were reported for using music to inform oneself about new music if the major activity reported was making music, working and studying, coping with emotions, relaxing and trying to fall asleep, or being on the move while listening to music. When a participant reported listening to music alone or while not interacting with other people, it was unlikely that music in the same situation was reported to fulfill updating functions. Having the possibility to choose the music and listening to music in the evening were also negatively associated with scores on this factor. In contrast, a higher level of reported arousal at the moment when participants decided to listen to music, as well as listening at night were positively associated with the factor score of *Updating One’s Musical Knowledge*.

On the B-S situational level, the only statistically significant activity was pure music listening, meaning that participants who reported to purely listen to music frequently showed a tendency to use music to update their musical knowledge and to feel connected to others who like the same music. In addition, positive associations were found for frequently listening to music while interacting with others, and for listening to music at night. Participants who frequently reported listening to self-chosen music had lower factor scores for *Updating One's Musical Knowledge*.

On the B-S personal level, liking *Pop* music showed a positive association, while liking *Rock & Metal* music was negatively associated with factor scores on *Updating One's Musical Knowledge*.

Killing time and overcoming loneliness. Ten significant predictors were included in the model on the W-S level. Four of these were negatively (activities: exercise, coping with emotions, party, and possibility of choice: concert), and six were positively associated (activity: being on the move, presence of others: alone, others present & no interaction, possibility of choice: radio, time of day: morning and afternoon) with scores on the factor Killing Time & Overcoming Loneliness.

On the B-S situational level, seven effects showed to be significant, all positively associated with the outcome variable. Participants who frequently reported listening to music while being on the move, doing housework, or working and studying on average showed higher factor scores for Killing Time & Overcoming Loneliness. The same was found for participants who frequently reported having the possibility to choose the music, listening to radio, listen to music in the evening, or listen to music because of their mood.

As for the B-S personal level, intensity of music preference, neuroticism, liking for the musical taste factors Techno & EDM, Volksmusik & Schlager, and Pop showed significant positive associations with scores on Killing Time & Overcoming Loneliness. Age showed a negative association, meaning that older participants reported less use of the time killing and overcoming loneliness functions of music listening.

Overall importance of the predictors. As the five models that were presented above provided a very detailed and rather complex insight into specific associations of person and situation variables with different functions of music listening, we also analyzed the overall importance of single variables with regard to the prediction of the functions of music listening using two indices. Figures 1a to 1c show results of the consistency and strength-of-association indices (I_F, I_R) for all predictor variables. Overall, the indices showed similar results. Activity, choice, and degree of attention were found to be the most important W-S situational predictors. The B-S situational predictors of

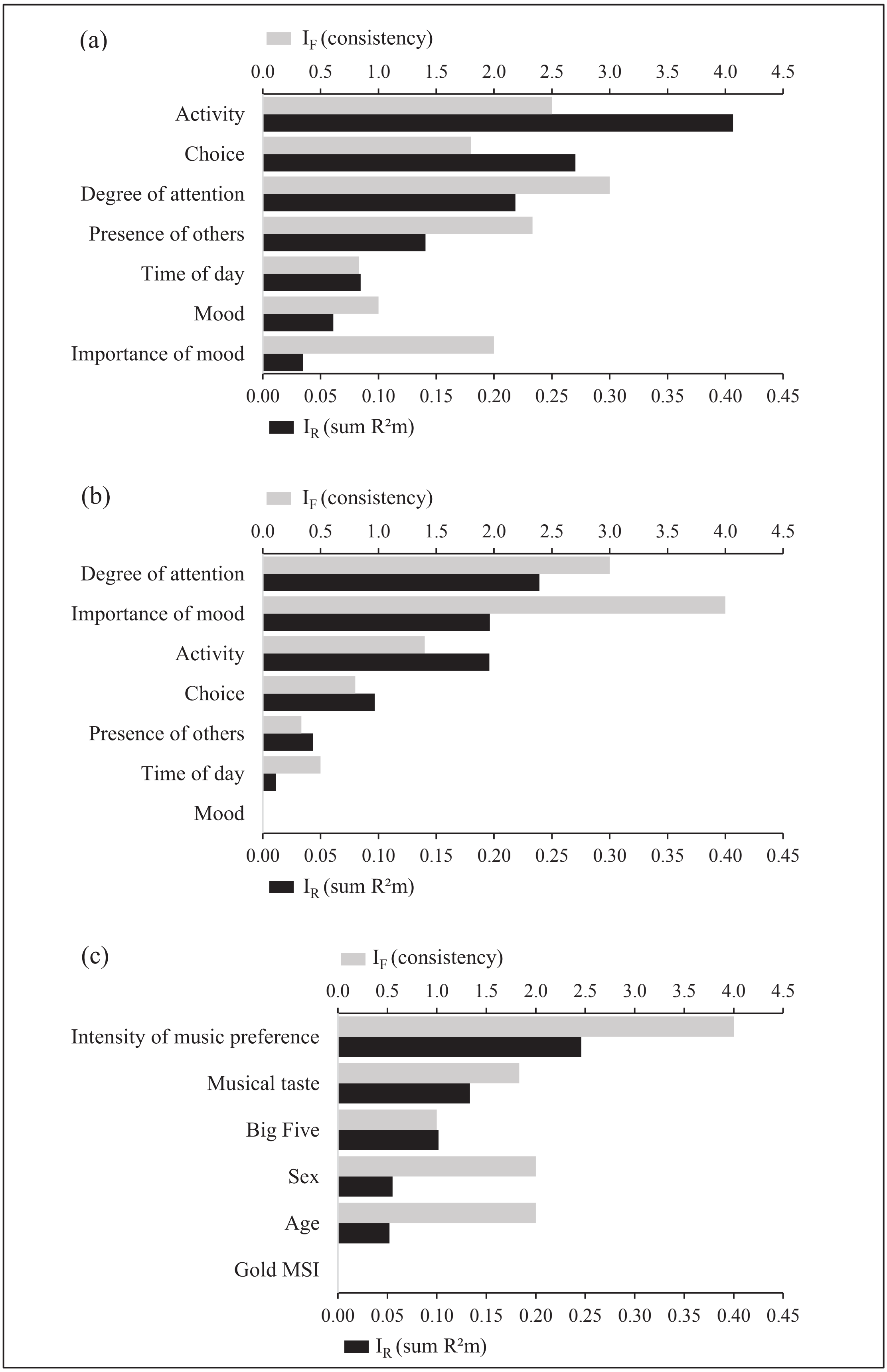

Figure 1. Consistency and strength of association indices for a) W-S situational b) B-S situational and c) B-S person related predictors.

degree of attention, importance of mood, and activity had the greatest impact, and intensity of music preference and musical taste were the most important B-S person-related predictors.

Variance explained. The amount of variance explained by the predictors in a specific model was assessed by calculating marginal and conditional R^2. Results are shown in Table 6. The five models explained between 29% and 42% of variance (34% on average) in the function factor scores. Similar to the ICCs, the amount of variance explained by situational and individual predictors also varied between models. Situational predictors explained between 9% and 24% of the variance of the factor scores. For example, situational variables varying within subjects explained 24% of variance in the factor Updating One's Musical Knowledge, while the B-S person-related predictors explained a much smaller amount of variance (1%) in that factor. For the factor Intellectual Stimulation, which showed a stronger association with individual differences, situational aspects explained 9% of factor score variance, whereas B-S person-related predictors explained 15% variance. On average, B-S situational predictors explained a larger amount of variance than B-S person-related predictors.

3.1.4 Discussion

We indicated that most research into the functions of music listening either focused on individual differences or on situational influences. Since all relevant variables appear simultaneously in real-life situations, our first aim was to investigate the relative impact of individual and situational influences on the functions of music listening. We used the findings of previous research to select the most relevant individual and situational factors, and integrated these into a comprehensive model in order to estimate their associations with functions of music listening in the context of all other variables. Our results revealed that functions of music listening varied considerably across situations. Moreover, our results showed that the relative contribution of situational and individual influences varied across the different functions of music listening. This suggests that some functions are affected more by individual differences, while others are more affected by situational influences. On average, the effects of situational characteristics were greater than the effects of individual characteristics (see Table 6).

Our second objective was to identify the most important variables that influence the functions of music listening. With regard to this aim, we found that each of the five functions we identified was associated with a specific set of predictor variables. Taken as a whole, a person's activity while listening to music was found to be the most influential situational variable explaining how people use music in a certain situation. Activity was followed by the possibility to choose the music and the degree of attention that was paid to music in that situation. Interestingly, for each factor of the functions of music listening, at least one activity was found to have a significant random effect, suggesting some variability in the effect of activity on functions of music listening between individuals. It can be expected that this between-person variability could be larger in studies that sample more situations than we did here. On the B-S level, the situational variables "degree of attention" and "importance of mood" were found to be the most important predictors. The fact that all effects of those two variables across the five models are positive indicates that people who generally pay more attention to music or who consider their mood very important in listening to music seem to get more out of music (i.e., they successfully use the functions of music listening). As for the B-S person-related variables, intensity of music preference and musical taste were found to be the most important predictors. These results are partly consistent with prior research that simultaneously investigated situational and person-related influences on music listening behavior (Krause & North, 2017). Krause and North (2017) also found that the current activity and the listener's general importance of music were very important in predicting music listening variables.

In our study, situational influences had a greater impact on the functions of music listening than individual differences. This contradicts findings by Lehmann (1993), who concluded that the listener always tries to listen to music in the same way (i.e., to fulfill the same functions of music listening in every single instance of music listening). Furthermore, our findings support the notion that people actively engage with music to fulfill specific functions in certain situations. These findings are thus in line with studies that tried to highlight the importance of situational aspects in research into the functions of music listening (Krause et al., 2014b; North et al., 2004). The significance of situational influences has several implications for research that restricts measurements of the functions of music listening on the level of the individual (e.g., clustering people in different listening typologies). Our results suggest that such differences between individuals do exist, but they explain much less variability than situational characteristics. Therefore, the result of clustering people by their functional use of music should be interpreted with caution, as listeners seem to strongly adapt their use of music to the situation they are in at a specific time. Future research of both sides (i.e., research investigating situational or person-related influences on music listening behavior) will strongly benefit from intertwining both research approaches (for an overview and detailed suggestions, see Fleeson & Noftle, 2008).

The specific results of the five different models bear several implications for future research investigating specific functions or effects of music listening. For example, intellectual stimulation often occurs when people are alone and listening to music attentively, whereas other functions occur while other people are around and the listener is performing a certain activity while listening to music. Experimental research almost entirely focuses on the very specific situation of people attentively listening to music alone. This condition exclusively implements a very specific set of functions of music listening, and results are not generalizable beyond this specific situation. Hence, the diversity of situational characteristics should be thoroughly considered when planning and conducting research on the functions or effects of music listening (e.g., emotional or motoric functions of music listening).

Our finding that some of the effects of different activities while listening to music on music listening functions showed individual variation (random effects) is in line with findings by Greasley and Lamont (2011), who similarly observed a large variation of the association between listening to music while working and the functions of music listening. Such individual differences in associations suggest that cross-level interaction effects might explain why some people are intellectually stimulated when listening to music while exercising and some are not. Therefore, future research should include investigations of cross-level interaction effects to explore potentially important person–environment interactions.

Even though all effects of our W-S and B-S situational variables point in the same direction, several predictors showed significance on attentively one of either level. As these differential effects can only be discovered if between- and within-person variance is clearly separated, we here claim that within-subject centering of level-one predictors is crucial to research differentiating individual from situational effects.

Neglecting this distinction might lead to biased effects and blurring of research findings.

Furthermore, in our study the B-S situational predictors (i.e., the mean values of the situational variables we measured in this survey) on average explained a larger amount of variance than the "classical" B-S person-related predictors such as Big Five personality dimensions or musical taste. This suggests that a large portion of the individual differences in functions of music listening might be explained by situation-related individual differences (e.g., the mean frequency of activities a person performs while listening to music) rather than by individual characteristics like personality traits or musical taste. Thus, these measures should be considered when investigating individual differences of the functions of music listening.

Importance of mood for the decision to listen to music showed to be a significant predictor of almost all functions of music listening on the B-S level, whereas specific mood states were not – neither valence nor arousal. In addition, specific mood states were only included in two models on the W-S level. We see three possible explanations for the absence of expected situational mood effects. First, our approach of retrospective assessments of three situations was not capable of reliably measuring specific mood states. Second, not a specific state of mood but some other person- or situation-related variable unrelated to mood might determine whether or not mood is important for functions of music listening. Third, the relatively broad dimensions of valence and arousal might be too non-specific and therefore not relevant for many of the functions of music listening investigated here. Measuring more specific emotional or mood states in future studies might help to find effects that were overlooked in the present study (for an interesting discussion, see Harmon-Jones, Bastian, & Harmon-Jones, 2016).

In addition to the many novel findings demonstrated here, we successfully replicated several findings of previous studies on both situational and individual levels, and as we controlled for a very broad set of influencing variables, we can assume that these effects are highly reliable. We will discuss a selection of effects in the following paragraphs.

The gender effect that we found for the factor *Mind Wandering & Emotional Involvement* is consistent with previous findings that show that female participants tend to use affective functions of music listening more than male respondents (Kuntsche et al., 2016).

We found a number of positive associations between the strength of music preference and functions of music listening on the between-subjects level. These findings provide further evidence for the notion that the more someone likes music in general, the more he/she uses almost all functions of music listening. However, this could also indicate a process in the opposite direction: The more someone uses almost all functions of music listening, the more he/she likes music in general (e.g., Schäfer & Sedlmeier, 2009).

Furthermore, we found an association between high neuroticism scores and the *Motor Synchronization & Enhanced Well-being* factor, which supports previous findings showing that people scoring high on neuroticism tend to use affect-regulating functions of music listening (Vella & Mills, 2017). It is important to mention that this association cannot be seen as a clear replication, as the *Motor Synchronization & Enhanced Well-being* factor is not about affect regulation only. In contrast, we did not observe an effect of openness to experience on the intellectual stimulation of music, which was in fact consistently shown by past research (e.g., Chamorro-Premuzic, Swami, et al., 2009).

Consistent with prior research investigating the role of choice on how people interact with music (e.g., Krause et al., 2014a; Krause et al., 2015), we also found the possibility to choose the music to be a very important factor influencing the functions of music listening. In detail, having the possibility to choose the music was positively associated with the factors *Intellectual Stimulation* and *Mind Wandering & Emotional Involvement*. These factors largely correspond with the “purposive listening” and “actively engaged listening” factors found by Krause et al. (2014a) and Krause et al. (2015), who also demonstrated positive associations between choice and these two factors. The pattern regarding the possibility of choice clearly shows that some functions of music listening require people to autonomously choose the music, whereas other functions do not. In general, our findings further emphasize the importance of having the possibility to choose music (i.e., choice and control) to the way people interact with music.

As was mentioned earlier, our present approach – integrating individual and situational variables into a comprehensive model to meet the complexity of real-life situations – calls for cross-level interactions (W-S × B-S). These interactions could be capable of explaining why several associations between situational influences and the functions of music listening varied across participants (i.e., revealed random effects). We decided against incorporating interaction effects here as our data includes three data points per participant only. However, our results revealed potentially valuable details for future research addressing cross-level interactions.

Furthermore, our survey relies on recollection of self-selected situations of our participants, that is, on memory representations. This method is vulnerable to bias due to memory effects as well as social desirability, and its ecological validity is limited. Due to the time limitations associated with an online survey, we limited our measurements to three situations per participant. Although we asked the participants to describe typical listening situations, we do not know whether or not these three reported situations are representative for each participant's overall listening situations. Hence, our findings should be replicated using methods with higher ecological validity and better representativeness of situations such as experience sampling or related methods (Hektner, Schmidt, & Csikszentmihalyi, 2007; Shiffman, Stone, & Hufford, 2008; Trull & Ebner-Priemer, 2013), which have recently been successfully applied to music-related research (e.g. Randall & Rickard, 2013). Such methods – collecting data in a participant's daily life – are virtually not affected by memory effects and allow the researcher to easily collect a multitude of data points per participant (Mehl & Conner, 2012).

The fact that we mainly recruited participants for our sample at German universities, and that it thus predominately comprises German students, prevents us from extending our findings and conclusions to other cultures. Future research should replicate this study in other cultures in order to investigate potential differences in the pattern of significant predictors of the functions of music listening.

It is also important to mention that some situations are inherently associated with certain forms of behavior or even with certain behavioral norms, which are often socially determined (Becker, 1963). These associations strongly depend on a person's individual interpretation of a situation (Goffman, 1974; Thomas, 1928). In the case of music, this for instance means that attendees of a classical concert (in a concert hall) collectively behave in the same way, that is, they sit still while attentively listening to the music (Burland & Pitts, 2014). On the one hand this means that some situations are closely associated with specific functions of music listening (e.g., listening to music in a music club socially suggests dancing), whereas other situations allow a greater degree of freedom with regard to the functions of music listening (e.g., listening to music at home alone). Furthermore, functions of music listening in reality are not only a causal result of situational and individual influences. People also actively change situations to enable certain functions of music listening. Due to this circularity, it becomes increasingly difficult to clearly differentiate between certain situations and functions of music listening and their causal relationships.

Moreover, providing a clear definition of what constitutes a situation is notoriously difficult. Recent psychological research differentiates between environmental cues (i.e., measurable situational objectives such as temperature, presence of others), psychological situations (i.e., the individual phenomenal experience of the situation, consisting of several situation characteristics), and situation classes (i.e., groups of situations which tend to share similar patterns, or constellations of characteristics; Rauthmann, Sherman, & Funder, 2015). Situational characteristics were found to be most important in predicting human behavior (Sherman, Rauthmann, Brown, Serfass, & Jones, 2015). Music psychology, however, almost exclusively focuses on situational cues (e.g., location, time of day). Future music psychological research should incorporate these findings and explore which special characteristics accompany a music listening situation.

Finally, the present paper did not address the question of which music with specific musical characteristics people are listening to in order to fulfill the various functions of music listening. To better understand the complex interactions that occur when a person listens to music in a specific situation, future research should investigate how music listening behavior (i.e., listening to pieces of music with specific musical characteristics) can be predicted by individual, situational, and functional variables.

This study is one of the first that integrates situational and individual variables in a comprehensive model – explaining why people listen to music in their daily lives. We identified the most important variables that affect engagement of people with music in daily life, and found that the functions of music listening vary considerably across situations and individuals. Our findings suggest that, overall, functions of listening to music seem to depend more on situational than on individual characteristics.

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3.2 Paper 2: Understanding music-selection behavior via statistical learning: Using the percentile-Lasso to identify the most important factors

The following chapter has already been published as a paper in the peer-reviewed journal *Music & Science* (Sage Publications) and is distributed under the terms of the Creative Commons Attribution 4.0 License.

Greb, F., Steffens, J., & Schlotz, W. (2018). Understanding music-selection behavior via statistical learning: Using the percentile-Lasso to identify the most important factors. *Music & Science, 1*(2), 1–17. doi:10.1177/2059204318755950

The paper was written together with Jochen Steffens (Technische Universität Berlin, Fachgebiet Audiokommunikation) and Wolff Schlotz (Max Planck Institute for Empirical Aesthetics). The text is presented here in its original wording as it was published in the journal (Postprint), so that some repetitions of the introduction above in the paper were inevitable. In order to achieve a consistent typographic style throughout the whole dissertation minor modifications have been necessary (e.g., changes to order and position of figures and tables). The passages referring to supplemental material that is available online were replaced with references to the appendix of the dissertation.

Understanding music-selection behavior via statistical learning: Using the percentile-Lasso to identify the most important factors

3.2.1 Introduction

> "What music does to people at different times, why they choose to listen to it so much, and why they choose a particular type of music while engaged in a particular activity – all of these are important unanswered questions" (Konečni, 1982, p. 500)

Although Vladimir Konečni wrote the statement above in 1982, many of these questions remain unanswered. Research investigating music-listening behavior in daily life usually follows one of two traditions, either focusing on individual differences (e.g., functions of music listening, music preferences), or investigating situational influences. The present study aims to bridge this gap by investigating the relative significance of variables from both the person-related and situational domains simultaneously. From this comprehensive perspective, we aim to identify the most important variables underlying music selection using methods from statistical learning theory to prevent overfitting and maximize predictive accuracy (Chapman, Weiss, & Duberstein, 2016).

Recent technical innovations allow the listener to listen to any kind of music in almost any situation, transforming music-listening behavior on two levels. First, engagement with music has become highly individual, and second, people now have the opportunity to listen to music in almost any everyday situation. These developments provide new opportunities for studying individual differences and situational influences of music-listening behavior, reflecting the major questions of the person-situation debate in personality psychology (see Fleeson & Noftle, 2008 for review). Following a synthesis approach, research on human behavior in daily life, including music listening, can potentially provide more reliable results and models by considering both levels of influence.

In music psychology, few studies on music-listening behavior to date have integrated both person-related and situational levels of influence. The following paragraph outlines the findings of those studies that did consider both levels. Krause and North (2017) have used person-related (e.g., sex, age, importance of music) and situational variables (e.g., time of day, activity) to predict music listening in a certain situation, how much choice people had in what they heard, how participants liked the music they were listening to, how engaged they were, and how arousing they perceived the music to be. Randall and Rickard (2017) developed a two-level model of personal music listening (i.e., listening via headphones) with regard to affective changes attributable to music listening. They found that affective changes due to music are almost entirely determined by the situation, whereas individual differences have only marginal effects. Furthermore, Greb, Schlotz, and Steffens (2017) explored the most important person-related and situational variables predicting functions of music listening (i.e., why a person listens to music in a certain situation). By quantifying the relative weight of individual and situational influences, they showed that music-listening functions are primarily attributable to characteristics of the situation. This predominance of situational influences on the goals and effects of music listening gives rise to a number of new questions. For example, what music do people select in order to accomplish their goals in a specific situation? What are the key variables ultimately driving individuals' music choices? Randall and Rickard (2017) shed some light on these questions by predicting the perceived emotional qualities of music using situational and person-related variables, but their characterization of music chosen by individuals was limited to the affective dimensions of valence and arousal. However, music perception comprises more characteristics, and these might be differentially influenced by situational and person-related variables (e.g., the tempo of a piece of music might be differentially perceived based on situational characteristics). Consequently, the present study focused on predicting a broader variety of subjective characteristics of music selected in daily life situations, such as tempo, melody, and complexity, by integrating variables related to listener, situation, and function of music listening.

3.2.1.1 Person-related variables

Previous research has found that demographic characteristics of listeners, their personality, musical taste, strength of music preference, and musical training are all potentially relevant variables contributing to music-listening behaviors. Demographic variables such as sex or age have consistently been shown to relate to music-listening behavior in daily life. For example, males under 34 years of age were found to visit live music events more often than females (Eventbrite & Media Insight Consulting, 2016) and also to purchase and download music more often (Aguiar & Martens, 2013).

With regard to the functions of music listening, research has consistently revealed that females tend to use music for affective functions (e.g., expressing feelings and emotions), coping, and enhancement (Boer et al., 2012; Chamorro-Premuzic, Swami, & Cermakova, 2012; Kuntsche, Le Mevel, & Berson, 2016), while men tend to use music for cognitive or intellectual reasons (Chamorro-Premuzic et al., 2012). Young people (10–34 years old) show a clear tendency to access recorded music via digital channels such as YouTube, digital streaming, downloads, or online radio (Eventbrite & Media Insight Consulting, 2016) and are more likely to access copyright-infringing music (Avdeef, 2012; International Federation of the Phonographic Industry, 2016). In contrast, people older than 30 years of age are more likely to use legal download sources, to buy CDs, and to listen to music on a CD player or via radio (Avdeef, 2012).

Ferwerda, Yang, Schedl, and Tkalcic (2015) demonstrated several relationships between personality and the way individuals browse and select music from streaming services. For example, individuals scoring high on Openness to experience are more likely to choose mood taxonomies offered by streaming services to browse through music collections, while individuals scoring high on Conscientiousness are more likely to use activity taxonomies. In addition, numerous studies linking personality dimensions (Big Five) with musical taste and preferences for certain musical styles indicate an indirect relation between personality dimensions and music-selection behavior (e.g., Greenberg, Baron-Cohen, Stillwell, Kosinski, & Rentfrow, 2015; Rentfrow, Goldberg, & Levitin, 2011; Rentfrow & Gosling, 2003). This indirect relation is supported by Dunn, de Ruyter, and Bouwhuis (2012), who found positive correlationsbetween individuals' musical taste and their actual listening behavior in daily life. Also, Greb et al. (2017) showed that fans of blues and jazz music tend to listen to music for intellectual stimulation, while fans of techno and electronic dance music tend to listen to music to move and enhance their well-being. Individuals who consider music to be an important part of their life tend to seek situations that involve music and are also more engaged with music when listening to it (Krause & North, 2017). Furthermore, Elpus (2017) showed that people who received school-based musical training and education are more likely to engage in musical activities such as playing an instrument or singing, while Stratton and Zalanowski (2003) found students majoring in music listened to a greater diversity of music than non-music majors.

3.2.1.2 Situational variables

Conceptualizing a situation is notoriously difficult; definitions and terminologies consequently vary between different research fields and even within the same field (for reviews see Rauthmann, 2015 or Rauthmann, Sherman, & Funder, 2015). Rauthmann et al. (2015) proposed a taxonomy that differentiates between situational cues (i.e., measurable situational properties such as time or weather), situational characteristics (i.e., the individual perception and experience of situational cues), and situational classes, which are abstract groups or types of situations based on similar cues or characteristics. In terms of this taxonomy, music psychology research on situational influences has mostly focused on cues such as location, activity, presence of others, or time of day.

Previous research has shown that the listening location influences goals and functions of music listening (North, Hargreaves, & Hargreaves, 2004). In addition, the effects of music listening and the experience of music vary by location type (Krause & North, 2017; Krause, North, & Hewitt, 2014). Furthermore, Krause and North (2017) found that type of location predicts the presence of music as well as perceived arousal of the music. Recent research has highlighted a person's activity while listening to music as the most influential situational variable for explaining how people use music in a specific situation (Greb et al., 2017). In addition, activity has been shown to be an important predictor of the presence of music, a person's engagement with music, and a person's experience of the arousing qualities of music in a given situation (Krause & North, 2017). Finally, Randall and Rickard (2017) found a negative association between traveling and perceived valence as well as a positive association between housework and the perceived arousal of the music heard. Research has consistently shown that the functions of music listening vary depending on the presence of others (Greb et al., 2017; North et al., 2004; Rana & North, 2007). For example, people tend to use music to pass the time or to support concentration when they are alone, but they use music to create a particular atmosphere when together with friends (Greb et al., 2017; North et al., 2004). These findings suggest that the presence of others also has an influence on the music chosen in a specific situation. Moreover, several studies have suggested that functions of music listening vary by time of day (Krause et al., 2014; North et al., 2004). For example, North et al. (2004) indicated that music is more likely to be used to help pass time during the workday (8:00 a.m. to 4:59 p.m.) than during the evening (5:00 p.m. to 11:00 p.m.). In another study by Krause and North (2017), participants were less likely to encounter music as the day progressed from morning to evening. It remains unclear whether these variations in the functions of music listening are also associated with specific musical choices, thus prompting the current study.

Besides the above-mentioned situational cues, there are also several concomitant person-related variables influenced by situations. For example, current mood as well as goals and functions of music listening have been shown to strongly vary by situation and also to impact musical choices. Recent daily life research has found a positive association between initial affective state at the moment a person decides to listen to music and perceived affective characteristics of the music selected, while controlling for a broad set of potential covariates (Randall & Rickard, 2017). While these results are supported by findings of several studies that reported similar mood-congruent music selection effects (Skånland, 2013; Thoma, Ryf, Mohiyeddini, Ehlert, & Nater, 2012), they are challenging several theories and an enormous body of research. This research states either that music is selected to moderate arousal to an optimal level (Konečni, Crozier, & Doob, 1976; Konečni & Sargent-Pollock, 1976) or that it is used to reach certain arousal-state goals, such as becoming energized during exercise (North & Hargreaves, 2000; for an overview of these opposing theories see Hargreaves & North, 2010). In general, further research is required to clarify the relationship between momentary mood and the music selected in daily life.

Music listening serves a number of functions beyond mood regulation (for an overview, see Schäfer, Sedlmeier, Städtler, & Huron, 2013). These functions have been shown to predominantly vary between situations (Greb et al., 2017) and to be associated with specific music styles (North et al., 2004). Randall and Rickard (2017) found that functions can be used to make predictions about the affective qualities of music selected at a certain time. More specifically, they found a negative association between the use of cognitive functions of music listening and the perceived (positive) valence of the music selected.

In order to understand the music selected to fulfill the various functions of music listening, the present study aimed to predict the characteristics of the music selected by considering the above-discussed listener and situationvariables. We had three specific objectives:

1. To investigate the relative influence of person-related and situational factors on music-selection behavior (i.e., estimating between- and within-person variance).
2. To control for a broad multivariate set of potentially influencing factors (i.e., the variables discussed above, for an overview see Figure 1) as they occur in reality in contrast to previous studies that predominantly have focused on bivariate relations of specific variables and music-listening behavior.
3. To identify key person-related and situational variables that reliably predict music-selection behavior in daily life using a statistical-learning approach that avoids overfitting of the statistical model.

To this end, we conducted an online survey asking participants to sequentially report three self-chosen listening situations typically occurring in their daily lives. For each listening situation, participants answered questions related to the situation, the music heard, and the functions of music listening. In addition, we measured multiple person-related variables (e.g., personality, musical taste).

3.2.1.3 Using statistical learning methods for variable selection

Given the numerous potentially relevant variables discussed above, we were faced with several challenges. Research consistently has shown that common model selection procedures such as stepwise procedures (including forward, backward, combined forward-backward, all possible subset selection) lead to overestimation of regression coefficients (Chatfield, 1995; Steyerberg, Eijkemans, & Habbema, 1999) and to selection of irrelevant predictors (Derksen & Keselman, 1992). These problems, known as overfitting, are more likely to occur with decreasing sample size (n) to predictor (p) ratio (Babyak, 2004; Derksen & Keselman, 1992). In general, as the number of predictor variables included in a model grows, so does the likelihood of finding relationships in sampled observations which are not present in the actual population (Babyak, 2004). Overfitting relates to the tendency of statistical models to mistakenly fit sample-specific noise (for reviews see Babyak, 2004; Hawkins, 2004) and might be one of the factors underlying the replication crisis in psychology (Yarkon & Westfall, 2017). An overfitted model is not going to produce reliable predictions on unseen data as it contains relations which are only present in the sample used to estimate the model and not in the general population. Therefore, avoiding overfitting when estimating statistical models was one of our core aims and is one of the primary objectives of the field of statistical learning. In recent years, statistical learning theory has developed several techniques to optimize models for the prediction of unseen data and to reduce overfitting. More specifically, regression regularization methods (also referred to as shrinkage methods) are often used in the context of the problem (Gareth, Witten, Hastie, & Tibshirani, 2015). The Lasso, originally proposed by Tibshirani (1996), has become a popular approach to variable selection in regression. It places a penalty on the regression coefficients, shrinking them all towards zero and sets some coefficients exactly to zero. The Lasso features a tuning parameter λ that controls the amount of shrinkage applied to the coefficients. The value of this tuning parameter is chosen using *K*-fold cross-validation, a technique of randomly splitting the set of observations into *K* folds of approximately the same size. Subsequently, *K*-1 folds (the training set) are used to estimate a statistical model, while the remaining fold (the validation set) is used to compute the mean squared error (*MSE*). In the regression setting, the *MSE* is given by

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (1)$$

where $\hat{y}_i$ is the prediction for the *i*th observation, and *n* is the number of observations. The *MSE* will be small if predictions are very close to the true value of *y*, and it will be large if predictions and true responses differ substantially. This procedure is repeated *K* times until every fold has been used as a validation set and results in *K* estimates of the test error, MSE_1, MSE_2, . . . , MSE_K. The K-fold cross-validation error is given by

$$CV_{(K)} = \frac{1}{K}\sum_{k=1}^{K} MSE_k \qquad (2)$$

The selection of the optimal tuning parameter λ_{opt} via cross-validation is based on a number series of λ values (grid). This grid should cover a range from zero, indicating no shrinkage and all predictors included in the final model, to λ_{max}, a value of λ for which all coefficients are set to zero and the model is empty. During the cross-validation process, a *K*-fold cross-validation error is calculated for each λ-value of the grid. Finally, the λ-value that yielded the smallest cross-validation error is chosen as

λ_{opt}. The Lasso can therefore be used for variable selection and does not impose the limitations of stepwise selection methods (Tibshirani, 1996; Whittingham, Stephens, Bradbury, & Freckleton, 2006).

As we needed to include numerous specific potentially relevant variables to predict an outcome, we had to address a high-dimensional regression problem (Chapman et al., 2016). In addition, we were not basing hypotheses on specific predictor-outcome associations. Therefore, we used a specific Lasso regression procedure that is suitable for this application as it is robust against overfitting, optimized to make predictions on unseen data, and has been specifically developed for multiple observations within clusters.

3.2.2 Method

3.2.2.1 Sample

Participants were recruited via mailing lists of German universities, posters at Goethe University Frankfurt, and Facebook. Respondents could enter a lottery to win a 15 Euro voucher for Amazon (chance of winning 1 in 10) as an incentive.

In total, 945 people began the study. Subsequently, 176 participants discontinued participation during the description of the first situation, 133 while describing the second situation, and nine while reporting the third and last situation. Additionally, 40 respondents did not follow the instructions, reporting multiple situations in the first text field. Consequently, we excluded these participants (N = 358; 38% of those who started the study) from the analyses. This exclusion rate is comparable to that of other online studies (e.g., Egermann & McAdams, 2013). The remaining 587 participants (58% female) included in the study had a mean age of 25.4 years (SD = 7.0). This final sample was characterized by rather minor deviations within one SD from age-specific average T-values based on a norm sample using a short version of the Big Five Inventory (Rammstedt, 2007). Despite being statistically significant (one-sample t-tests: all ps < .01), deviations of sample means were minor for Agreeableness (T = 51) and Extraversion (T = 49), while average Conscientiousness (T = 44) and Neuroticism (T = 44) scores were moderately lower, and Openness scores moderately higher (T = 56) than the norm-based average.

3.2.2.2 Design and measures

The questionnaire covered four areas: the situation, the functions of music listening in the specific situation, music characteristics, and personal information (see Appendix I).

The situation section asked several questions about the participants' ability to choose the music, presence of others, and time of day (see Appendix I Section A).

The music individuals listened to in specific situations was characterized via seven-step bipolar rating scales. Specifically, we asked for familiarity (unknown–known), liking (I do not like–I like a lot), and seven musical characteristics, namely: *calming–exciting*, less *melodic–very melodic*, *less rhythmic–very rhythmic*, *slow–fast*, *sad–happy*, *simple–complex*, *peaceful–aggressive*. These musical characteristics were compiled by a group of experts, including musicologists, music psychologists, and audio engineers, with the objective of easily describing music in daily life. For the purpose of avoiding unsystematic variance in the data, participants alternatively could check *unspecific/I do not know* for each of these items (see Appendix I Section B).

Functions of music listening were measured by factor scores on five factors described by Greb et al. (2017). These factors are based on 22 items capturing a wide range of functions of music listening that could vary across different situations (see Appendix I Section C), labeled *Intellectual Stimulation*, *Mind Wandering & Emotional Involvement*, *Motor Synchronization & Enhanced Well-Being*, *Updating One's Musical Knowledge*, and *Killing Time & Overcoming Loneliness*. As previous research has indicated that a listening experience might involve multiple functions (e.g., Greasley & Lamont, 2011), we assessed all functions for each situation.

In addition, we gathered the following person-related information: gender, age, Big Five personality traits using the BFI-10 (Rammstedt, Kemper, Klein, Beierlein, & Kovaleva, 2013), and intensity of music preference measured by a six-item inventory (Scha¨fer & Sedlmeier, 2009). We also assessed musical training using the third scale of the Gold-MSI consisting of seven items (Schaal, Bauer, & Müllensiefen, 2014) and musical taste via an inventory described in Greb et al. (2017) that captures six taste dimensions: *Blues & Jazz* (blues, jazz, funk, soul, reggae), *Techno & EDM* (techno, EDM, house, rap/hip-hop), *Other Cultures & Latin* (other cultures, Latin, world music, classical), *Volksmusik & Schlager* (German "Volksmusik" and German "Schlager"), *Pop* (pop), and *Rock & Metal* (rock, metal). This inventory also allows participants to indicate if they are not familiar with a certain style of music. For these styles, no liking ratings were collected (see Appendix I Section D). For a schematic overview of all variables reported in the present study, see Figure 1.

3.2.2.3 Procedure

The data were collected through the same survey used by Greb et al. (2017). While Greb et al. (2017) investigated the effect of personal and situational factors on why people listen to music in a specific situation, the current investigation is focused on the effect of situational and personal factors on the actual music that is selected in a specific situation. Therefore, the present study uses another subset of situations and additional variables (i.e., music selected in a specific situation) that were not analyzed by Greb et al. (2017).

Data were collected online (browser-based) through Unipark/EFS Survey software (Questback GmbH). After clicking the participation link or scanning a QR code from a poster, participants were redirected to the online survey. The welcome page informed participants about the general procedure and focus of the study, the voluntariness of participation, their ability to discontinue the study at any time, and the opportunity to take part in a lottery to win a voucher. Thereafter, the task of the survey – to sequentially describe three self-selected situations in which participants typically listen to music – was explained. First, participants were asked to describe the specific situation in a concise sentence with as much as detail as necessary. Then, participants answered questions regarding the situation, the music, and functions of music listening in that specific situation (see Appendix I Sections A to C). These three sections were successively answered for each of the three situations. Subsequently, participants reported on person-level variables (Appendix I Section D). Finally, if desired, they could provide their email address to take part in the raffle to win the Amazon voucher.

3.2.2.4 Data analysis

As our aim was to analyze music-selection behavior, we excluded all situations in which participants indicated that they did not have any control about the music present in a given situation (excluded categories: possibility of choice “no” [85 situations] and

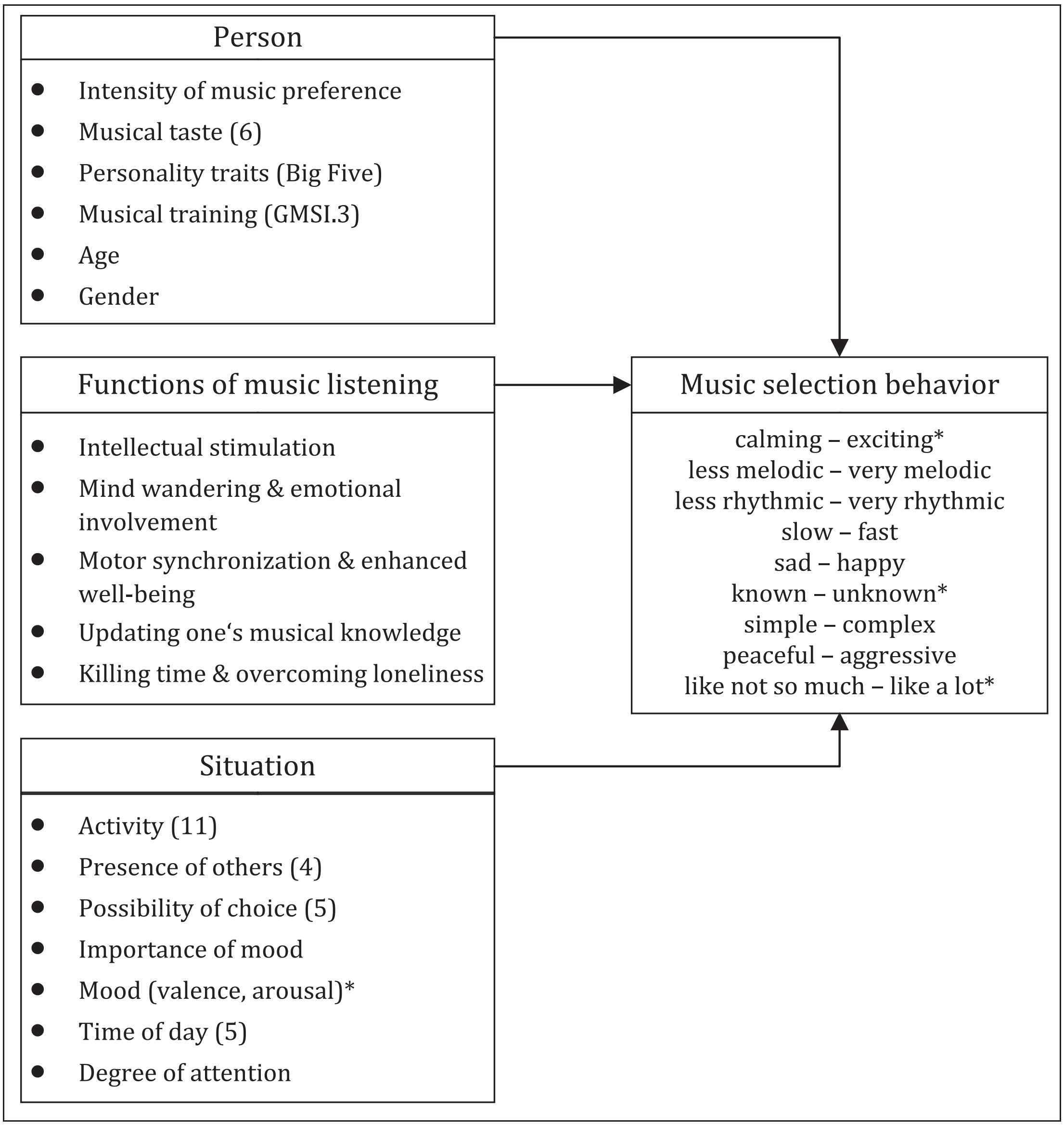

Figure 1. Variables measured in the online survey.
Person-related variables were measured once, while functions of music listening, situation, and music selection behavior were reported for each of three situations. Numbers in parentheses indicate the number of categories or dimensions a variable included.
* indicates variables which have been excluded from the main analysis due to problematic distributions or too many missing values (see data analysis for details).

"unspecific" [94 situations]). The final data included 1,582 situations from 586 participants.

As reported in Greb et al. (2017), each individual situation description was classified into one of 11 activity categories, and listening location was discarded due to high correlations between activity and location categories. Table 1 provides the activity category labels, descriptions, and relative frequencies.

Based on the high number of missing values, which were due to the response option of *unspecific/I don't know*, we excluded valence (400 missing values, 25% of total data) and arousal (342 missing values, 22% of total data) from the major analysis. We calculated separate analyses investigating the effects of valence and arousal because we expected them to be important variables. The results are reported separately. In addition, we excluded familiarity, liking and *calming–exciting* from the analysis due to skewed distributions. This finally resulted in six outcome variables considered in the present analysis: *less melodic–very melodic*, *less rhythmic–very rhythmic*, *slow–fast*, *sad–happy*, *simple–complex*, *peaceful–aggressive*. For each outcome variable, we excluded all cases in which participants selected *unspecific/I don't know*.

Situational cues, functions of music listening, and characteristics of the music heard were measured three times per person, creating a two-level structure of measures (situations) nested within persons. We therefore used multilevel linear regression modeling, as it allows the inclusion of time-varying (i.e., situation-related) predictors and the analysis of unbalanced designs, while at the same time accounting for non-independence of observations within subjects. Categorical variables were included as dummy variables (coded as 0, 1). All within-person predictors (i.e., all responses that were measured separately for each situation) were centered at each person's mean to avoid any confounding effects with between-person variability (Enders & Tofighi, 2007).

As one of our aims was to identify the most important variables predicting music-listening behavior (i.e., musical characteristics people choose to listen to) and due to the high number of independent variables (Figure 1) we used a percentile-Lasso regression method for generalized linear mixed models. Recent research has shown that the optimal value of the tuning parameter λ (λ_{opt}) chosen by cross-validation (and therefore also the final model) is extremely sensitive to the fold assignment of the cross-validation procedure (Krstajic, Buturovic, Leahy, & Thomas, 2014; Roberts & Nowak, 2014). To overcome these limitations, we implemented the percentile-Lasso method proposed by Roberts and Nowak (2014). This method deals with the problem of fold sensitivity by using repeated cross-validation, leading to less variation in λ_{opt}. In detail, the percentile-Lasso selects λ_{opt} from a set of optimal values (derived from each cross-validation cycle) by calculating the θ-percentile of this set. In most circumstances, $\theta = 0.95$ produces good and reliable results (Roberts & Nowak, 2014).

Table 1. Explanation and descriptive statistics of the 11 activity categories.

Activity while listening	Description	% of total activities
Being on the move	Situations in which the main activity was being on the move (e.g. by car, subway, or bike).	30.3
Housework	Situations in which the main activity was doing any kind of housework (e.g. washing up, cleaning, getting ready).	15.5
Working & studying	Situations in which the main activity was either working, learning, or studying.	13.8
Others	Situations which could not be coded to one of the other categories.	11.0
Pure music listening	Situations in which the main activity was listening to music only.	7.3
Relaxing & falling asleep	Situations in which the main activity was relaxing, getting new energy, or trying to fall asleep.	6.9
Exercise	Situations in which the main activity was exercising or doing sports.	5.8
Party	Situations in which the main activity was celebrating or dancing in a club or disco (dancing which was mentioned in a training context was coded as Exercise).	4.5
Coping with emotions	Situations in which the main activity was coping with own emotions.	2.5
Making music	Situations in which the main activity was playing or making music.	1.3
Social activity	Situations in which the main activity was interacting with others (e.g. cooking and eating with friends, or playing with friends).	1.2

Note. Each situation described in free response format (N = 1,582) was classified into one of the activity categories.

In addition, the percentile-Lasso allows the implementation of the “one-standard-error” (1-*SE*) rule to select λ_{opt}. The main purpose of the 1-*SE* rule, as proposed by Hastie, Tibshirani, and Friedman (2009), is to choose the most parsimonious model whose accuracy is comparable with the best model. The 1-*SE* rule is applied by selecting the largest value of λ whose corresponding cross-validation error is within one standard error of the minimum cross-validation error as λ_{opt}.

In our data analysis, we repeated 100 ten-fold cross-validations. For each cross-validation cycle, the optimal value of λ according to the 1-*SE* rule was calculated. From this set of 100 potentially optimal values, the 95th percentile was selected as the final λ_{opt}. For each outcome variable, we determined the value of λ for which all coefficients were set to zero (λ_{max}) by successively increasing λ by 1 until the condition was met.[1]

[1] It is also possible to estimate λ_{max} using the dual norm (for a discussion see Bach, 2011).

Then, an individual λ_{max} value was taken as the maximum grid value for each model. We used a grid length of $K = 100$ and an exponential form for the grid to achieve higher resolution of values towards 0. More specifically, we used the following grid for all models:

$$\lambda_k = \frac{1}{2}\left(\exp\left(\frac{k}{K-1}\ln(2\lambda_{max}+1)\right)-1\right) \tag{3}$$

with $k = 0,1,2, \ldots, K-1$

where λ_k denotes the k-th element of the grid, K is the grid length, and λ_{max} the value of λ where all predictors were set to zero. As suggested by Tibshirani (2013), we calculated the null space of each predictor matrix and found the null vector for all matrices. This ensured that the Lasso solutions were unique.

We applied this procedure to each outcome variable separately, leading to six final models. All calculations were performed using the glmmLasso package (Groll, 2017) within the development environment R-Studio (RStudio Team, 2015) of the software R.3.0.2 (R Core Team, 2015). For our categorical variables (which were entered as dummy-coded variables), we used a group Lasso estimator as proposed by Groll and Tutz (2014). It applies the same amount of shrinkage to all dummy variables that constitute one categorical variable (e.g., the variable time of day is constituted by early morning, morning, noon, afternoon, evening, and night). Therefore, the Lasso either completely includes a categorical variable (i.e., all constituting dummy variables) or completely excludes it from the final model (for more detailed information see Meier, Van De Geer, & Bühlmann, 2008; Yuan & Lin, 2006). Estimation of p-values for non-zero coefficients was based on re-estimation and Fisher scoring as implemented in glmmLasso (Groll, 2017).

In accordance with Roberts et al. (2016), we took the nested structure and the number of data points per participant into account when randomly splitting the data into 10 folds (i.e., into training and validation sets) for cross-validation. We decided to randomly split our data at the level of the individual (Level 2). Therefore, any training and validation set contained measurements from the same person, and the models were optimized to predict values of unseen individuals. This approach does not allow the inclusion of random effects of Level 1 predictors but should lead to highly reliable fixed effects. We calculated the repeated cross-validation error as the mean of the cross-validation error across 100 repetitions as a measure of fit index. This index is small if the predicted responses are close to the true responses. In addition, we calculated marginal R2 as proposed by Nakagawa, Schielzeth, and O'Hara (2013) after re-estimating the final model using the lme4 (Bates, Maechler, Bolker, & Walker, 2015) and the MuMIn (Barton, 2016) packages. Marginal R2 indicates the proportion of variance explained by the fixed effects.

3.2.3 Results

3.2.3.1 Situational vs. person-related influences on characteristics of music selected

Intra-class correlation coefficients (ICCs) based on an intercept-only model for each musical characteristic are shown in Table 2. Intra-class correlation coefficients indicate the amount of variance attributable to person-related and situational levels. For the six musical characteristics studied here, ICCs varied between .09 for *fast–slow* and .32 for *peaceful–aggressive*. The ICC for *fast–slow* indicates that between-person differences accounted for 9% of the variance, while within-person differences between situations accounted for 91% of the variance. Across all models, between-person differences on average accounted for 23% and within-person differences between situations for 77% of the variance, signifying high variability within individuals and the potentially important role of situational characteristics in the music selections of individuals.

3.2.3.2 Predicting characteristics of music selected

Figure 2 shows the coefficient paths of the percentile-Lasso and λ_{opt} based on repeated cross-validation for the six musical characteristics, illustrating how coefficients of predictors tend towards zero with a growing amount of shrinkage (i.e., with growing λ). When a predictor is set to zero, it is eliminated from the model. When λ_{max} is reached, all coefficients are set to zero. For the musical characteristics *melodic* and *rhythmic*, only one predictor was selected, while multiple predictors were included for

Table 2. Multilevel estimations of within and between subject effects for musical characteristics. Predictors selected by the percentile-lasso with repeated 10-fold cross-validation (CV) (see text for details).

Parameter	Estimate (*SE*)					
	less melodic – very melodic[a]	less rhythmic – very rhythmic[b]	slow – fast[c]	sad – happy[d]	simple – complex[e]	peaceful – aggressive[f]
ICC	.28	.22	.09	.18	.29	.32
λ_{opt}	328.84	421.55	89.3	103.28	62.82	52.20
λ_{max}	376	560	771	436	575	602
Repeated 10-fold CV error	1.93	1.82	1.49	1.45	1.97	1.94
Marginal R^2	.04	.09	.35	.23	.28	.24
Situational predictors						
			Fixed effects			
Activity						
Being on the move			.15 (.33)	.05 (.35)		.22 (.31)
Housework			-.03 (.10)	-.05 (.11)		-.05 (.11)
Working and studying			-.26 (.13)*	-.18 (.14)		-.38 (.13)**
Pure music listening			.10 (.16)	-.19 (.16)		.18 (.17)
Party			-.23 (.19)	.29 (.27)		.39 (.21)
Relaxing and falling asleep			-.79 (.17)***	-.38 (.18)*		-.80 (.17)***
Exercise			.42 (.16)**	-.01 (.17)		.92 (.17)***
Coping with emotions			-.40 (.24)	-1.90 (.23)***		.81 (.26)**
Making music			-.16 (.38)	-.45 (.42)		.20 (.37)
Social activity			.42 (.33)	.25 (.33)		.10 (.32)
Presence of others						
Alone			-.13 (.08)	-.23 (.08)**		-.27 (.08)**
Others present and no interaction			.03 (.12)	-.09 (.13)		-.30 (.13)*
Others present and interaction			.15 (.23)	.23(.25)		-.13 (.22)
Possibility of choice						
Yes					.27 (.10)**	
Radio					-.30 (.18)	
Concert					.30 (.24)	
Importance of mood						
Degree of attention			.06 (.03)*	-.03 (.03)	.07 (.03)**	.06 (.03)*
Time of day						
Early morning						.03 (.09)
Morning						-.03 (.09)
Noon						.13 (.11)
Afternoon						.19 (.09)*
Evening						-.24 (.08)**

(continued)

Table 2 (continued)

Parameter	Estimate (*SE*) less melodic – very melodic[a]	less rhythmic – very rhythmic[b]	slow – fast[c]	sad – happy[d]	simple – complex[e]	peaceful – aggressive[f]
Functions of music listening						
Intellectual Stimulation	.59 (.06)***		-.49 (.07)***	-.09 (.08)	.61 (.07)***	-.25 (.07)***
Mind wandering and emotional involvement				-.26 (.08)***	.30 (.07)***	
Motor synchronization and enhanced well-being		.79 (.05)***	.91 (.06)***	.73 (.07)***		.59 (.07)***
Updating ones musical knowledge			.38 (.06)***	.30 (.06)***	-.25 (.06)***	.18 (.06)**
Killing time & overcoming loneliness			-.13 (.07)			-.14 (.07)*
Person-related predictors						
Intensity of music preference			.09 (.04)**		.15 (.04)***	
Musical taste						
Blues and Jazz			-.20 (.04)***			
Techno and EDM			.14 (.04)***		-.07 (.05)	
Other cultures and Latin						
Volksmusik and Schlager					-.15 (.05)***	
Pop					-.33 (.05)***	
Rock and Metal			.10 (.04)*		.15 (.05)**	.24 (.05)***
Personality traits						
Openness to experience					.09 (.06)	
Conscientiousness						
Extraversion						
Agreeableness					-.13 (.05)*	
Neuroticism					-.14 (.05)**	
Age						
Sex[g]						.56 (.10)***
Musical training						
Random effects						
SD intercept	.86***	.84***	.63***	.70***	.81***	.91***

Note. *SE* = standard error; ICC = intra-class correlation coefficient; CV = cross-validation; EDM = electronic dance music; *SD* = standard deviation.
[a] n = 1318 observations within 547 persons. [b] n = 1330 observations within 547 persons. [c] n = 1270 observations within 537 persons. [d] n = 1196 observations within 525 persons. [e] n = 1210 observations within 524 persons. [f] n = 1262 observations within 536 persons. [g] 0 = female; 1 = male.
* $p < .05$. ** $p < .01$. *** $p < .001$

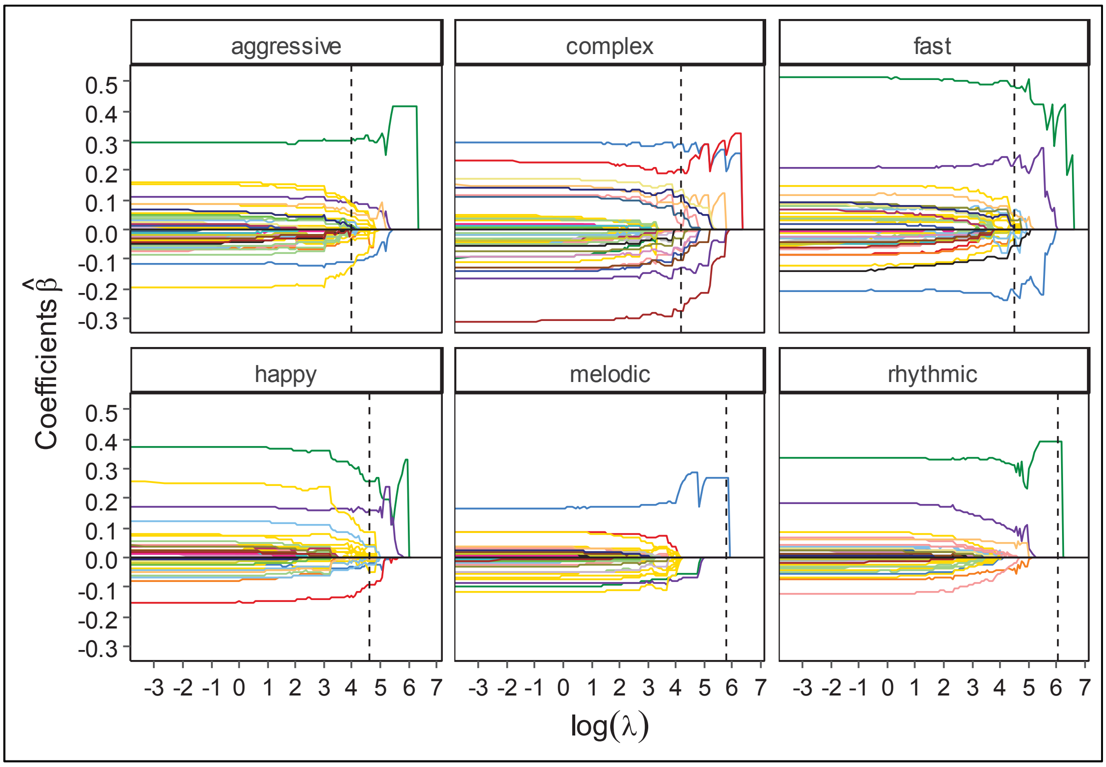

Figure 2. Coefficient paths of the percentile-Lasso models for six musical characteristics. The x-axis shows log of λ; the y-axis shows penalized regression coefficients. Each line represents a specific regression coefficient. Dummy variables pertaining to one variable share the same color. Starting from the left, λ is very small (virtually no penalization) and all predictors are included in the model. Moving from left to right the amount of shrinkage increases and coefficients tend towards zero. Predictors are eliminated when they hit the horizontal "0" line. The optimal value of the tuning parameter λ (λ_{opt}) is shown by the vertical dashed line.

the other models. The development of regression coefficients also illustrates their interdependence. More specifically, some coefficients rise when other coefficients are set to zero.

Table 2 shows the maximal grid values (λ_{max}), the optimal tuning parameter λ_{opt}, the repeated cross-validation error, marginal R^2, and the estimations of regression parameters for predictor variables included in the six models. The repeated cross-validation error varied between 1.45 for *sad–happy* and 1.97 for *simple–complex*, and marginal R^2 ranged from .35 for *slow–fast* to .04 for *melodic*. Whereas the cross-validation error of *sad–happy* indicates the best model in terms of predictions on unseen data, the model *slow–fast* had the highest proportion of explained variance, with the largest marginal R^2. The number of selected variables fell between 1 for *melodic* and *rhythmic* and 13 for *complex*. On the level of situational variables, functions of music listening were included in all six models, *degree of attention* in four models, and *activity* and *presence of others* in three models. Variables most often included on the person-related level were *musical taste* (included in three models) and *intensity of music preference* (included in two models). In contrast, personality traits and gender were only present in one model each, while age and musical training were not included in any model. The following sections provide a more detailed overview of the predictors included in each of the six models separately for situational and person-related levels.

3.2.3.3 Situational variables

The five factors of functions of music listening was the only group of variables included in all six models. When participants reported listening to music for intellectual stimulation, they tended to listen to more melodic, less fast, less happy, more complex, and less aggressive music. *Mind wandering and emotional involvement* was related to less happy and more complex music. Participants tended to choose more rhythmic, faster, happier, and more aggressive music when wanting to move and enhance their well-being. *Updating one's musical knowledge* led to faster, happier, less complex, and more aggressive music choices. Slower and less aggressive music was used to pass the time and overcome loneliness.

With regard to the activities included in the six models, the analyses revealed several findings. Music reported for working or studying was less fast, less happy, and more peaceful. For relaxing and falling asleep, participants reported listening to slower, less happy, and less aggressive music. While *exercise* was associated with faster and more aggressive music, *coping with emotions* was related to less fast, less happy, but also more aggressive music.

Participants reported a tendency to listen to slower, less happy, and more peaceful music when alone. Situations in which others were present (without communication) showed a similar pattern, differing only in a faster tempo of the music in comparison to that chosen when alone.

Given freedom of choice, participants were likely to select more complex music. In contrast, listening to the radio was associated with less complex music choices.

Moreover, the degree of attention participants reported to pay to the music was related to faster, less happy, more complex, and more aggressive music. However, the relationship between the degree of attention and the happiness of the music did not reach significance in the re-estimation step.

The time of day was only included in the predictive model of *peaceful–aggressive*, indicating that listening to music in the afternoon was related to more aggressive music choices, whereas music listening in the evening was associated with less aggressive music.

As mentioned in the data analysis section, we repeated the complete analyses with the data set, including valence and arousal to determine whether they would be selected by the percentile-Lasso. This analysis revealed valence and arousal to be included in two models. Reported valence (positive mood) at the moment of the decision to listen to music was associated with happier ($\beta = .21$, $p < .001$) and more complex music ($\beta = .08$, $p = .02$). When participants reported relatively high arousal when deciding to listen to music, they tended to select faster ($\beta = .10$, $p < .001$) or more aggressive music ($\beta = .07$, $p = .02$).

3.2.3.4 Person-related variables

Musical taste factors were included in three out of the six models, revealing several individual differences. In detail, participants who endorsed enjoying *Blues and Jazz* tended to listen to slower music, while fans of *Techno and EDM* reported a tendency to listen to faster and less complex music. Whereas fans of *Pop* and *Volksmusik and Schlager* tended to listen to less complex music, participants who reported liking *Rock and Metal* were disposed to listen to music with increased tempo, higher complexity and more aggressiveness. Participants with high intensity of music preference reported listening to faster and more complex music. The personality traits of Openness to experience, Agreeableness, and Neuroticism remained in one model only, predicting the selection of simple versus complex music. Specifically, participants scoring high on Openness to experience tended to listen to more complex music, while those with high Agreeableness and Neuroticism scores leaned towards less complex music. Finally, men reported listening to more aggressive music than women.

3.2.4 Discussion

This study investigated the relative influence of person-related and situational factors on music-selection behavior in daily life by integrating a broad set of potentially important variables in comprehensive models. A statistical learning procedure (percentile-Lasso) optimized for predicting unseen data was used to identify the key variables of both levels influencing the selection of music with defined characteristics by individuals within specific, comprehensively characterized situations. Findings demonstrated that the characteristics of music selections predominantly varied within persons, that is, between situations. However, both the relative contribution of situational and individual effects as well as the number of predictor variables contributing to music selection varied, indicating that some characteristics mainly vary between situations while others are more affected by individual differences. Notably, functions of music listening was the only group of variables that was included in each model, and hence can be seen as the most important situational variables with regard to a broad set of characteristics of music selected in specific situations. Although less broadly represented, musical taste factors was also found to be an important group of variables explaining individual differences in music-selection behavior in three out of six models. Taken together, 29 situational and 14 person-related predictors were found to contribute to the prediction of unseen data, clearly reflecting the importance of variance attributable to situational differences. Due to the fact that all models were optimized to make predictions on unseen persons, the effects found should be highly reliable.

The significance of situational factors found in the present study is consistent with current research showing that functions of music listening and affective changes in response to music are mainly influenced by the listening situation (Greb et al., 2017; Randall & Rickard, 2017). For example, the ICC of .18 we found for the *sad–happy* outcome variable is close to findings from a recent experience sampling study by Randall and Rickard (2017), who reported an ICC of .14 for valence of music selected (*negative–positive*). This highly situational selection behavior might be explained in part by recent technological developments that provide music listeners with high degrees of freedom for listening to all kinds of music in almost any situation.

The detailed patterns uncovered by the present investigation suggest that people's music-selection behavior is mainly driven by the functions of music listening, degree of attention a person pays to the music, current activity, and the presence of others while listening. These findings are partly consistent with Randall and Rickard (2017), who demonstrated strong associations between functions of music listening, activity, and the actual music selected. Randall and Rickard (2017) also found cognitive reasons for listening – which are broadly comparable to our *intellectual stimulation* factor – to be associated with the selection of less positive/happy music.

Our finding that musical taste was an important variable explaining individual differences of music-selection behavior complements findings by Dunn et al. (2012) who reported positive correlations between liking for musical styles and listening durations for these styles. Our results indicate that musical taste (measured via liking for musical styles) is also related to preferences for certain characteristics of music listened to in daily life. Nevertheless, the amount of variance attributable to between-person differences for all musical characteristics was lower than the amount of variance attributable to situational differences. This contradicts the common belief that individuals' music-selection behavior is mainly driven by musical taste.

The fact that Big Five personality traits were only selected in one out of six models indicates a rather weak association between personality traits and music-selection behavior in daily life. This finding is in line with a recently conducted meta-analysis by Schäfer and Mehlhorn (2017) showing that Big Five personality traits cannot substantially account for variance between individuals in musical taste and preferences. We found associations only between personality traits and the selection of complex music. Our finding that Openness to experience is positively associated with the selection of complex music is consistent with Schäfer and Mehlhorn (2017) who demonstrated a positive correlation between Openness and the liking for more complex musical styles.

The current study focused on musical characteristics selected in specific situations. Hence, we could not determine which style of music people selected in everyday life, so further research is needed in this area. This would aid in examining how people differ in their selection with regard to different styles and also check for within-style variability (e.g., Rentfrow et al., 2012). It may be that a person constantly listens to a favorite style of music but selects music with different musical characteristics within that style based on the situation. Nevertheless, Rentfrow et al. (2012) conclude that individual differences in musical preferences are largely based on sonic characteristics of the music. From this, one would also expect large individual differences with regard to musical characteristics selected in daily life. This is contrary to our findings, which show rather small individual variations.

Results from our separate analysis of the role of current mood on music-selection behavior complement the findings by Randall and Rickard (2017), who demonstrated that people generally tend to select mood-congruent music. We found positive associations between valence (positive mood) and the selection of happier and more complex music, as well as between arousal and the selection of faster and more aggressive music. These four musical characteristics go beyond the analysis of music selection by Randall and Rickard (2017) that limited its measurement to perceived valence and arousal of the music. Nevertheless, the characteristics found to be associated with current mood in our study can be interpreted in the framework of valence and arousal: happier music is likely to be perceived as more positive, while faster, more aggressive, and more complex music is likely to be perceived as more arousing. From this perspective, our results reflect mood-congruent selection of music. In contrast to Randall and Rickard (2017), however, not all of our outcome variables were associated with current mood. For example, current mood was not related to the selection of more melodic or more rhythmic music in our analysis. This might be due to our more differentiated measurement of characteristics of music selected (six musical characteristics) compared to perceived valence and arousal of the music as used by Randall and Rickard (2017). In general, our findings provide a detailed picture of the relationship between current mood and music selected and largely support the notion that people select mood-congruent music. This conclusion is also supported by the finding of a negative association between *coping with emotions* and the selection of less happy music in our study.

Interestingly, person-related variables were included in just three models (*slow–fast*, *simple–complex*, *peaceful–aggressive*). As demonstrated by ICCs, the models of music complexity and aggressiveness showed the strongest associations with individual differences, and the model predicting selection of fast music showed the highest amount of variance within individuals (i.e., a minimum of between-person variance). This raises the question as to why no person-related predictors were selected in the remaining models (*less melodic–very melodic*, *less rhythmic–very rhythmic*, *sad–happy*) despite considerable between-person variance in these outcomes. It is likely that highly relevant traits for these outcome variables were not represented by our measures of individual differences. For example, there is some evidence that trait empathy is associated with the selection of sad music (e.g., Vuoskoski, Thompson, McIlwain, & Eerola, 2012) and that alexithymia may explain individual differences in the perception of emotions expressed by music (Taruffi, Allen, Downing, & Heaton, 2017).

Another remarkable result was the varying number of predictor variables included in each model. The extreme parsimoniousness of the models predicting the selection of very melodic or very rhythmic music might indicate an important role of individual differences. Some situational associations for those two variables might vary between individuals, which could be accounted for by including random slope parameters in the mixed-effects regression models. These individual deviations from the overall slope means might be best explained by cross-level interactions (i.e., person x situation interaction effects). For instance, individuals scoring high on Extraversion might tend to listen to more complex music while working and studying, while persons scoring low on Extraversion might tend to select simpler music (Furnham & Allass, 1999). We decided against the inclusion of random slopes and interaction effects on the basis of very limited numbers of observations within participants in our sample (max. three data points per participant), which would make model estimation unstable and potentially unreliable. Hence, future research could benefit from the inclusion of random slopes, implying that a larger number of situations should be sampled per individual.

The variation of repeated cross-validation errors and marginal R^2 values across the different models clearly shows that high R^2 values are not necessarily associated with small repeated cross-validation errors (i.e., good predictions on unseen individuals). For example, while the model predicting the selection of slow–fast music revealed the highest marginal R^2 of .35, the model showing the best prediction on unseen individuals (*sad–happy*) revealed a marginal R^2 value of .23. In addition, the two models *melodic* and *rhythmic*, both of which contained only a single predictor, yielded comparable or even slightly better repeated cross-validation errors than the two models predicting *complex* and *aggressive* music (both containing several predictors). On one hand, this highlights the importance and reliability of the single predictors in the models *melodic* and *rhythmic*. On the other hand, it might indicate slightly overfitted models for complex and *aggressive*, despite our use of the 1-*SE* rule that protects against overfitting.

In addition, the present investigation demonstrated that innovative statistical learning techniques can effectively be used to inform psychological research. We believe that the analysis of intensive longitudinal data from studies of daily life that include large numbers of potentially interacting variables would strongly benefit from such techniques. For example, using cross-validation methods could lead to higher reliability of variable selection due to avoidance of overfitting. The concept of optimizing models by predicting unseen data is a core strength of statistical learning procedures. The use of such methods prevents the researcher from overfitting by optimizing R^2 and therefore is likely to result in more precise estimation of effects. In addition, R^2 values represent better estimations of the true values in the general population of interest (for an overview, see Yarkoni & Westfall, 2017). This characteristic of statistical learning procedures partially explains the rather low marginal R^2 values of some of our models, and is likely to be a consequence of more precise estimations.

As mentioned in the introduction, defining what constitutes a situation is a difficult endeavor. Following the taxonomy proposed by Rauthmann et al. (2015), current research clearly shows the significance of situational characteristics (i.e., the individual perception and experience of situational cues) for the prediction of human behavior (Sherman, Rauthmann, Brown, Serfass, & Jones, 2015). On a higher level, situational classes form abstract groups or types of situations based on similar cues or characteristics. This study, as well as most of the other studies dealing with situational influences on music listening, used measurements of situational cues and characteristics to investigate situational effects. However, it might be more beneficial to attempt to cluster situational cues and characteristics into situational classes. By combining several situational cues and characteristics, such classes could provide a more abstract and condensed form of situational variable. These could then be used to make predictions about music-listening behavior, thereby saving the researcher from interpreting seemingly endless single associations between certain situational variables and behavioral outcome variables of interest. In addition, some situations are normatively related to specific functions of music listening and to specific music characteristics. For example, music in a dance club is intended to evoke movement, and it is very likely to be rhythmic and fast. From this perspective, a more abstract level of situation, as given by situational classes, would provide an opportunity to clearly differentiate such normative situations from situations in which people have greater freedom to choose music.

Our study comes with a number of limitations. First, our data result from retrospective self-report and are therefore vulnerable to memory effects, social desirability, and other biasing factors. This also implies that ecological validity might be limited, even though the reports were based on daily life situations. As mentioned earlier, we collected a maximum of three data points per participant. While this allowed us to estimate within-subject effects (i.e., situational effects), additional data points would have led to more precise estimations with potentially higher representativeness for participants' daily lives. This limitation was deliberate in order to minimize the time required to complete the online survey and avoid threats to data quality. Although we asked participants to describe listening situations that typically occur in their daily lives, we do not know how representative the three situations were of a participant's actual behavior. Hence, future research should replicate our findings using methods with higher ecological validity and better representativeness of situations, such as ambulatory assessment or related methods (Hektner, Schmidt, & Csikszentmihalyi, 2007; Randall & Rickard, 2013; Shiffman, Stone, & Hufford, 2008; Trull & Ebner-Priemer, 2014). Such methods usually collect momentary data in participants' daily lives; momentary reports are virtually unaffected by memory effects and provide intensive longitudinal data with potentially high representativeness (Mehl & Conner, 2012). In addition, the use of such methods will provide more complete situational data compared to our approach of measuring recollections of typical situations, as we had to offer an unspecific response option for some variables, which resulted in a relatively high proportion of missing values.

Second, the present study relates to the measurement of music characteristics, which was based on participants' reports. As the perception of these characteristics might vary between individuals (e.g., Taruffi et al., 2017), future research should broaden the measurement of music selected by supplementary measures, such as objective musical features obtained by music-information retrieval (e.g., loudness, tempo) or musical styles selected. This could offer further insights and would provide answers to additional questions, such as: Do subjectively reported characteristics correlate with objectively derived characteristics of music selected? Do fans of certain styles of music predominantly listen to their favorite styles in everyday life? However, individual music selection is based on individual perception. Therefore, subjective measurements such as those applied in our study should be complemented, but still included, in future studies investigating music-selection behavior.

Third, due to the fact that, to the best of our knowledge, no package or software solution exists that is able to perform a Lasso regression on a multivariate multilevel model, our approach does not account for covariations between our six outcome variables. Hence, it is important to mention that our results of modeling predictors of different musical characteristics are based on independent models. A single multivariate model might lead to slightly different results.

Taken together, the present study demonstrates that music-selection behavior strongly varies between situations within individuals. This situational variability was best explained by situation-specific functions of music listening, while musical taste was found to be the most important variable explaining differences on the individual level. In general, a better understanding of which music people listen to in different situations to accomplish certain listening goals might help experimental researchers to properly select music for the investigation of specific functions or effects of music listening. Future research should integrate situational variables into research design in order to provide optimal conditions for investigating specific effects of music as well as to increase the reliability and external validity of results.

3.2.5 References

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3.3 Paper 3: Modeling Music-Selection Behavior in Everyday Life: A Multilevel Statistical Learning Approach and Mediation Analysis of Experience Sampling Data

The following chapter was submitted for publication in the peer-reviewed journal *Journal of Personality and Social Psychology* (APA). This paper has not been peer reviewed. Please do not copy or cite without author's permission.

> Greb, F., Steffens, J., & Schlotz, W. (2018). Modeling music-selection behavior in everyday life: A multilevel statistical learning approach and mediation analysis of experience sampling data. Manuscript submitted for publication.

The paper was written together with Jochen Steffens (Technische Universität Berlin, Fachgebiet Audiokommunikation) and Wolff Schlotz (Max Planck Institute for Empirical Aesthetics). The text is presented here in its original wording as it was submitted to the journal, so that some repetitions of the introduction above in the paper were inevitable. In order to achieve a consistent typographic style throughout the whole dissertation minor modifications have been necessary (e.g., changes to order and position of figures and tables). The passages referring to supplemental material were replaced with references to the appendix of the dissertation.

Modeling Music-Selection Behavior in Everyday Life: A Multilevel Statistical Learning Approach and Mediation Analysis of Experience Sampling Data

3.3.1 Introduction

Music listening in recent years has become a highly individualized activity. The rapid growth of music digitalization and mobile music listening devices, such as smartphones and music streaming services, provide individuals with the freedom to listen to almost any kind of music during their daily life (Berthelmann, 2017; Gesellschaft für Konsumforschung, 2017). Given this freedom of choice, people indeed tend to actively select and use music to accomplish specific goals in certain situations (DeNora, 2000; Krause, North, & Hewitt, 2015). In contrast to the widespread use of new technological developments by music listeners, little is known about the processes underlying the selection of music in daily life, and scientific research about music listening in everyday life still is underdeveloped. To some extent, the high degree of complexity due to the large amount of contributing factors and their interactions has led to this lack of current knowledge. Thus, the goal of the current study was to explain this complexity when people actively select music in their daily life. In particular, we aimed to identify personal and situational variables of high relevance for music-selection behavior, and to integrate these factors into a comprehensive model predicting music selection while strictly avoiding overfitting. This also includes an investigation of the role that functions of music listening play in the selection of music. By using the experience sampling method, we captured almost unbiased behavioral data representative of participants' daily lives. We used statistical learning procedures for variable selection to make predictions of unseen data and avoid overfitting (Yarkoni & Westfall, 2017). Clarifying the role of listener, situation, and functions of music listening in music selection aids in the understanding of why people listen to music in certain situations and how situational and person-related factors govern the selection of music and its characteristics. This knowledge helps to answer the question of who listens to what kind of music in which situation and why, and might contribute to an improvement of music recommendation systems.

3.3.1.1 Contributions of Person and Situation to Music-Listening Behavior

Past research on music listening mostly focused on one of two major determinants of music-listening behavior, namely influences of individual or situational factors. Research on individual differences mainly seeks to answer questions such as why some people predominantly listen to aggressive rock music, whereas others prefer listening to smooth jazz (Delsing, ter Bogt, Engels, & Meeus, 2008; Gardikiotis & Baltzis, 2012) or why some individuals mainly listen to music for intellectual stimulation and others use it for mood regulation (e.g., Chamorro-Premuzic & Furnham, 2007). This research revealed a large number of significant associations between music listening and person-related variables, particularly age, gender, personality traits, musical taste, and musical training (e.g., Boer et al., 2012; Chamorro-Premuzic, Swami, Furnham, & Maakip, 2009; Cohrdes, Wrzus, Frisch, & Riediger, 2017; Ferwerda, Yang, Schedl, & Tkalcic, 2015; Greenberg, Baron-Cohen, Stillwell, Kosinski, & Rentfrow, 2015; LeBlanc, Jin, Stamou, & McCrary, 1999).

Complementary research investigating situational influences on music listening mainly focused on situational cues, such as location, activity, presence of others, and time of day (e.g., Krause & North, 2017a, 2017b; Krause, North, & Hewitt, 2014; North, Hargreaves, & Hargreaves, 2004).

Since both person and situation usually influence behavior at the same time, investigating variables of both domains simultaneously is of high importance. Combining this synthesis approach proposed by Fleeson and Noftle (2008) with daily-life research methods (Conner & Mehl, 2012) can potentially provide more reliable results as well as more valid conclusions and behavioral predictions. Integrating both levels of variance better reflects the complexity of the multitude of factors interacting in daily life. The simultaneous investigation of individual and situational influences also allows an estimate of the amount of variance explained by both domains. In music psychology, research integrating person-related and situational factors is scarce. The few existing studies indicated that both domains are important for explaining the presence of music (Krause & North, 2017b), emotional responses to music (Randall & Rickard, 2017), or functions of music listening in different situations (Greb, Schlotz, & Steffens, 2017). Up to now, only one study specifically addressed music-selection behavior (Greb, Steffens, & Schlotz, 2018). This study showed that the characteristics of selected music are largely attributable to situational influences and it revealed a detailed pattern of variables being associated with the selection of music (Greb et al., 2018). Functions of music listening referring to the intentional use of music to accomplish specific goals were the most important variables for predicting music selection (Greb et al., 2018). However, the study relied on retrospective self-reports of three listening situations obtained via an online survey, potentially introducing bias to the data.

Functions of music listening also vary by situation and are largely influenced by the activity performed while listening to music (Greb et al., 2017). In addition, functions were shown to reliably predict music selection in specific situations (Greb et al., 2018; Randall & Rickard, 2017). Hence, functions of music listening might mediate music selection in daily life, such that activity or mood determines why a person wants to listen to music in a given situation, whereas the subsequent process of selecting a specific musical piece is largely driven by these functions of music listening. Thus, the specific role of musical functions in the process of music selection needs further clarification.

3.3.1.2 Methodological Challenges

Investigating music-selection behavior in daily life is associated with considerable methodological challenges. First, measuring real-life behavior requires a suitable data collection method. Many of the studies mentioned above used retrospective data collection based on online surveys or laboratory studies, which are relatively easy to conduct but are limited in their ecological validity and are likely to be biased in several ways (e.g., memory biases, limited representativeness of situations). The gold standard of investigating real-life behavior in ecologically valid settings leading to almost unbiased data is the collection of data in people’s daily life. To measure subjective perceptions and experiences involved during music listening and selection, the experience sampling method (ESM) was identified as a suitable method (Greasley & Lamont, 2011; Hektner, Schmidt, & Csikszentmihalyi, 2007; Randall & Rickard, 2013; Sloboda, O'Neill, & Ivaldi, 2001). ESM provides a multitude of data points per participant that allows the investigation of between- (i.e., person-related) and within-subject (i.e., situational) variance (Hektner et al., 2007). The widespread distribution of smartphones makes it easier to conduct ESM studies compared with the past when people had to carry around large extra devices (e.g., palmtop computers).

Second, a data collection method investigating person-related and situational factors simultaneously needs appropriate statistical models. Multilevel modeling (MLM) is the most appropriate for analyzing nested or longitudinal data, as it allows modeling of several levels of variance simultaneously and estimation of the relative impact of person-related and situational factors on the outcome variable (Nezlek, 2008). Particularly, ESM data with its nested structure in combination with MLM can be used to build reliable models to predict real-life behavior (Fleeson, 2007). In music psychology, this possibility has often been neglected and ESM data were averaged at the listener level while ignoring situational variance (e.g., Greasley & Lamont, 2011; Juslin, Liljeström, Västfjäll, Barradas, & Silva, 2008).

Third, the proposed approach of investigating person-related and situational factors in an integrative model inevitably leads to a large number of variables to be included in the analysis (e.g., Greb et al., 2018; Randall & Rickard, 2017). Consequently, the question of which variables should be selected as the most significant predictors of behavior becomes an important issue. Commonly used selection procedures, such as all sorts of step-wise regression, are highly problematic as they often lead to overestimation of regression coefficients and tend to select irrelevant predictors (Derksen & Keselman, 1992; Flom & Cassell, 2007; Steyerberg, Eijkemans, & Habbema, 1999; Whittingham, Stephens, Bradbury, & Freckleton, 2006). These problems—also known as overfitting—are addressed by the field of statistical learning, which has developed a broad set of methods and procedures to overcome such limitations (Babyak, 2004; Chapman, Weiss, & Duberstein, 2016). Many of these methods provide new opportunities to enrich psychological research (Chapman et al., 2016; Yarkoni & Westfall, 2017). For instance, the Lasso, originally proposed by Tibshirani (1996), offers a promising alternative to common variable selection procedures. As the Lasso is applicable on linear regression and multilevel linear regression models, it is especially useful if researchers aim to interpret model coefficients, as is often the case in psychological research. Notably, the issue of overfitting and the application of statistical learning to overcome such limitations have rarely found its way into music psychology. In the context of music listening in daily life, only one study has successfully applied cross-validation and a Lasso algorithm for variable selection to find the most significant predictors of music-selection behavior (i.e., Greb et al., 2018). However, Greb et al. (2018) employed retrospective assessments and a very limited variety of situations, which might facilitate biased results despite appropriate statistical analysis based on statistical learning.

3.3.1.3 The Present Research

We sought to explore music-selection behavior in daily life by investigating situational and person-related factors simultaneously. Given the research findings and theoretical considerations above, our research was guided by the model shown in Figure 1. To take the multitude of potentially influential factors in all domains (person, situation, functions) into account simultaneously, we built comprehensive models by including a broad set of variables. With the greater objectives of avoiding overfitting and maximizing predictive accuracy, our study had the following research aims:

1. Investigate the relative contribution of person-related and situational variables to variance in daily-life music-selection behavior (i.e., estimating between- and within-subject variance components).
2. Identify the most important variables involved in the process of music selection as outlined in Figure 1 (i.e., detect all relevant direct effects).
3. Identify the potential mediating role of functions of music listening in the association of situational and person-related variables with music selection.
4. Explore whether effects of situational variables on music selection vary across individuals by testing for individual differences in the associations identified earlier (i.e., effects resulting from research aim 2).
5. As we consider replication to be an important aspect of our research, we aimed at comparing the results of the current study using daily-life research methodology to those of another study that used the same statistical approach but was based on retrospective reports of very few music listening situations (i.e., Greb et al., 2018).

To address these aims, we conducted an experience sampling study in which participants reported on their music listening using smartphones. Participants reported on situational cues, the music they heard, and on functions of music listening. In addition, we collected a broad set of person-related variables in an initial laboratory session. Our study design is an improvement of a current study in which we investigated all direct effects on music selection in daily life (Greb et al., 2018). To address the methodological problems discussed in the introduction and to be able to compare results, we applied the same statistical learning procedure (i.e., percentile-Lasso) as Greb et al. (2018).

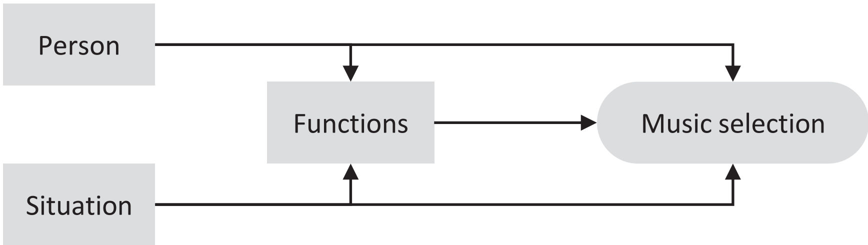

Figure 1. Model of music selection guiding the current investigation

3.3.2 Method

3.3.2.1 Sample

In total, 119 participants (54 men, 65 women; mean = 24.4 years; SD = 4.4) were recruited via the participant database of the Max Planck Institute for Empirical Aesthetics in Frankfurt am Main (Germany). To ensure sufficient within-subject variance, we only included participants who indicated listening to music for at least two hours a day for a minimum of five days per week. People received 25 € for voluntarily participating in the study. Depending on the amount of valid responses to prompts, each participant could receive a graded bonus of up to 25 € (for details see the procedure section).

3.3.2.2 Measures

Prescreening. Frequency of music listening in daily life was measured by two items: (1) "How often do you listen to music during the week?" (response scale: less than once a week to more than seven times a week; nine scale points); and (2) "On average, how long do you listen to music per day?" (response scale: less than half an hour to more than four hours; nine scale points). Additionally, we asked participants to report if they owned a smartphone and, if yes, which operating system is running on their device (Android, iOS, Windows Mobile, Blackberry, other).

Person-related variables. In addition to age and gender, we assessed musical sophistication using the German version of the Gold-MSI (Schaal, Bauer, &

Müllensiefen, 2014), the intensity of music preference using six items from Schäfer and Sedlmeier (2009), musical taste using liking ratings for 19 musical styles (see Greb et al., 2017 for details), and the Big Five personality traits using a German version of the IPIP-NEO-120 (Johnson, 2014) compiled from a subset of items described in Treiber, Thunsdorff, Schmitt, and Schreiber (2013). For the musical taste ratings, we computed sum scores based on the factor structure reported by Greb et al. (2017). As the questions about musical taste included the possibility to select "I don't know" for a musical style, we used imputation to replace missing data with the mean value of the ratings of the respective musical style.

ESM measures. Each assessment started with the initial question "Are you listening to music right now?" If the answer was "no", the assessment was finished; if the answer was "yes", it continued. The remainder of the assessment consisted of three sections about the situation, the music, and the functions of music listening in the current situation. The first section asked participants to indicate how long they have been listening to music already, what their main activity was using a list of categories developed by Greb et al. (2017), if other people were present, if they chose the music, and how much control they had in what music they were listening to (see Appendix II for exact wording and response scales). Additionally, we asked for their mood at the time they decided to listen to music (valence and arousal (Russell, 1980)). We also asked how important participants considered their mood state for the decision to listen to music and how much attention they were paying to the music. The second section included questions about musical characteristics as well as the composer/interpreter, name of the piece, and musical style. First, participants reported on the volume (quiet–loud) and their liking of the music (I like it less–I like it a lot) on seven-step bipolar rating scales. Musical characteristics were measured by seven items from Greb et al. (2018) on bipolar rating scales with seven scale points, but here we added one item (intensity) for completeness, resulting in the following list of items: *calming–exiting*, *slow–fast*, *sad–happy*, *less melodic–very melodic*, *less rhythmic–very rhythmic*, *simple–complex*, *peaceful–aggressive*, *less intense–very intense*. Additionally, we asked for familiarity of the music (unknown–known) and asked the participants to differentiate whether they listened to vocal or instrumental music. Furthermore, we requested participants to name the specific piece, the artists, or the musical style they were listening to at the time of measurement. Given the wide range of different styles people might listen to, we used an open-ended response format, as this was shown to suit this kind of questions best (Greasley, Lamont, & Sloboda, 2013). The third section about functions of music listening used a subset of functions developed by Greb et al. (2017). The 15 items (3 per dimension) used here mainly covered functions about intellectual stimulation, mind wandering & emotional involvement, motor synchronization & enhanced well-being, updating one's musical knowledge, and killing time & overcoming loneliness (all items are listed in the Appendix II). Lastly, we computed sum scores based on the factor structure reported by Greb et al. (2017).

The following variables were not part of the current analyses: duration of music listening at time of measurement, familiarity of the music, liking of the music, instrumental/vocal music, and free responses on musical pieces, artists, and styles.

3.3.2.3 Sampling Design and Hardware

The prescreening was completed online through Unipark/EFS Survey software (Questback GmbH, 2015). Person-related variables were reported on a tablet computer (Samsung Galaxy Tab A 1.7) in the laboratory. The ESM measures (daily-life assessments) were presented using movisensXS, Version 1.0.1 (movisens GmbH, 2015), a smartphone application for Android specifically programmed for ESM studies. Participants used either their own smartphone or a loan device (Motorola Moto G3) to run the application.

The study ran for ten consecutive days (Friday–Sunday). Participants each received 14 alarms within an individual 14-hour time window per day. The number of alarms was pretested in a pilot study and was considered acceptable by our pretesting candidates. The alarms occurred randomly within the pre-selected period with a minimum time of 20 minutes between each alarms. Participants were instructed to answer as many alarms as possible, but they could postpone (by 5, 10, or 15 min) or reject alarms. In addition to this strictly time-based sampling plan, we implemented an event-based plan to capture as many music listening situations as possible. Participants were encouraged to start the assessment manually when they were listening to music by pressing a button in the movisensXS application.

3.3.2.4 Procedure

Participants received an e-mail containing an individual participation link. After clicking on the link, they were redirected to an online survey and answered the first questionnaire (prescreening). Participants who fulfilled the inclusion criteria for attending in our main study (i.e., reported listening to music on average for a minimum of two hours a day for at least five days a week) could choose a date for their first session in the lab. People who did not meet the inclusion criteria were informed that they could not participate in the study and were thanked for their time. Depending on whether participants owned a smartphone with the respective operating system, they were informed that they could use their own device or that they would receive a smartphone for the duration of the study. At their first appointment in the lab, participants completed the questionnaire containing the person-related variables. Afterwards they were informed about the general procedure of the ESM study. Participants who owned an Android smartphone were asked if they were willing to use their own smartphone for the study. All others received a loan device with movisensXS as the only usable application installed. Participants who decided to use their own device received free wireless internet access and guidance for downloading and installing movisensXS from the Google Play store. Thereafter, a demo version of the study was transferred and started. Participants were shown how to accept, delay, or reject an alarm and then simulated a situation in which they were listening to music and answered the items. When participants were familiar with the questionnaire and the handling of the application, they were asked to indicate three 14-hour periods between 00:01–23:59 they were willing to receive alarms. We chose three blocks—Monday–Thursday, Friday & Saturday, and Sunday—as we expected people to get up earlier during workdays and eventually stay up longer on Friday and Saturday. People were free to choose different periods or use the same period for all assessment days. The event-based (button-pressed) assessments could also be activated outside of the individually selected periods. Participants then received details about the reimbursement. To encourage the participants to answer as many alarms as possible, we decided to employ a graded system. People received 25 € for their participation when answering less than 50% of random alarms. For each additional 1%–10% of answered alarms they received 5 € extra. This led to a maximum compensation of 50 € if 90%–100% of all alarms were answered. Participants were explicitly instructed that any answer—including “no” I do not listen to music—was counted as an answered alarm to avoid false reporting of music-listening situations to receive higher compensation. Event-based (button-pressed) assessments were not considered for the calculation of the reimbursement. Finally, participants received a small booklet that contained information about the study and contact addresses should they encounter problems.

In the final lab session—after the10 days of experience sampling—the researcher controlled and transferred the data of the movisensXS application. At this time, participants completed a short evaluation questionnaire and received their reimbursement. Finally, participants received assistance with de-installing movisensXS from their smartphone.

3.3.2.5 Data Analysis

As the major aim of the study was to predict music-selection behavior (i.e., active selection of music), we excluded all situations in which participants indicated that they did not have any control about the music in a given situation (“How much control do you have in what you hear?” 1 = Any control). In addition, we excluded situations in which participants did not choose the music (“Did you choose the music?” “No”) or listened to music at a club or in a concert. The final data included 2,674 situations reported by 119 participants.

Time data was centered at each participant’s earliest response to a random trigger depending on weekdays and weekends. As participants were free to report music listening at any time (button-pressed), very few listening events (3%) were reported shortly before an individual’s earliest random trigger. We decided to treat button-pressed events in close proximity to a participant’s centering time as “getting up earlier”, whereas time stamps earlier than two hours before an individual’s centering time were considered as “still being awake”. For example, when a participant’s earliest answer to a random trigger was 7am, an answer at 8:30 was counted as 1.5, an answer at 6:30 as -0.5, and an answer at 4:30 am was counted as 21.5.

The resulting ESM data reflects a three-level structure (i.e., situations nested within days nested within persons). We checked the different levels of variance and decided not to include days as a separate level, as days explained only minor variability in the outcome variables. The resulting two-level model also is less complex and more readily comparable with that reported by Greb et al. (2018). In addition, the Lasso implemented in the glmmLasso package (Groll, 2017) used here and by Greb et al. (2018) cannot estimate three-level models.

We used multilevel linear regressions to model our data, as it allows the analysis of unbalanced designs and the inclusion of time-varying (i.e., situation-related) predictors, while accounting for non-independence of observations within participants. All variables that varied at the within-subject level were centered at the person-mean to clearly differentiate levels of variation (Enders & Tofighi, 2007).

As we considered the sampling of situations within participants to result in a good representation of a person's episodes of music listening in daily life, we also took aggregated measures of all situational variables into account (e.g., average level of valence or arousal). These aggregated measures can be used to predict individual differences in music-selection behavior.

We used intercept-only models to estimate the intraclass correlation coefficient (ICC), which indicates variance components of person and situation levels for functions of music listening and music selection.

To identify the most important variables and to explore all direct effects involved in the music selection process as outlined in our model (Figure 1), our analysis consisted of four steps. These steps followed the logic of a classical mediation analysis as proposed by Baron and Kenney (1986), but considered multiple predictors simultaneously. Step A tested all direct effects of person- and situation-related variables on music selection (i.e., y on x), step B tested all relevant direct effects of person- and situation-related variables on functions of music listening (i.e., m on x), and step C tested all direct effects of musical functions on music selection (i.e., y on m). Finally, step D tested all direct effects of person, situation, and musical functions on music selection (i.e., y on x and m). Step D represents a replication of the statistical analysis by Greb et al. (2018). Throughout these analyses, we implemented the percentile-Lasso method proposed by Roberts and Nowak (2014), using the 95th percentile for variable selection. We repeated 100 five-fold cross validations with a random sample split for each repetition. For each outcome variable, we determined λ_{max} by successively increasing λ by one until all coefficients were set to zero. We then used a linear λ grid of length 100 running from λ_{max} to zero. Data was split into training and test set at the level of the individual (Level 2), such that models were optimized to make predictions on unseen participants (Roberts et al., 2016). The following lines illustrate model equations entered into the percentile-Lasso procedure for Step D, which includes all covariates analyzed here (see Appendix II for model equations of steps A, B, and C):

Level 1:

$$\begin{aligned} Y_{ij} = \ & \beta_{0j} + \beta_1 \,\mathrm{time}_{ij} + \beta_2 \,\mathrm{time}_{ij}^2 + \beta_3 \,\mathrm{weekend}_{ij} + \beta_4 \,\mathrm{valenceC}_{ij} \\ & + \beta_5 \,\mathrm{arousalC}_{ij} + \beta_6 \,\mathrm{imp.of.moodC}_{ij} + \beta_7 \,\mathrm{attentionC}_{ij} \\ & + \beta_8 \,\mathrm{activity1C}_{ij} + \cdots + \beta_{18} \,\mathrm{activity11C}_{ij} \\ & + \beta_{19} \,\mathrm{presence.of.others1C}_{ij} + \beta_{20} \,\mathrm{presence.of.others2C}_{ij} \\ & + \beta_{21} \,\mathrm{intel.stimulationC}_{ij} + \beta_{22} \,\mathrm{mind.wanderingC}_{ij} \\ & + \beta_{23} \,\mathrm{motor.synchronizationC}_{ij} \\ & + \beta_{24} \,\mathrm{updating.musical.knowledgeC}_{ij} + \beta_{25} \,\mathrm{killing.timeC}_{ij} \\ & + R_{ij} \end{aligned} \tag{1}$$

Level 2:

$$\begin{aligned} \beta_{0j} = \ & \gamma_{00} + \gamma_{01} \,\mathrm{valenceM}_j + \gamma_{02} \,\mathrm{arousalM}_j + \gamma_{03} \,\mathrm{imp.of.moodM}_j \\ & + \gamma_{04} \,\mathrm{attentionM}_j + \gamma_{05} \,\mathrm{activity1M}_j + \cdots + \gamma_{015} \,\mathrm{activity11M}_j \\ & + \gamma_{016} \,\mathrm{presence.of.others1M}_j + \gamma_{017} \,\mathrm{presence.of.others2M}_j \\ & + \gamma_{018} \,\mathrm{sex}_j + \gamma_{019} \,\mathrm{age}_j + \gamma_{020} \,\mathrm{intensity.musicpreference}_j \\ & + \gamma_{021} \,\mathrm{musical.taste1}_j + \cdots + \gamma_{026} \,\mathrm{musical.taste6}_j \\ & + \gamma_{027} \,\mathrm{big5.1}_j + \cdots + \gamma_{031} \,\mathrm{big5.5}_j + \gamma_{032} \,\mathrm{gold.msi1}_j + \cdots \\ & + \gamma_{036} \,\mathrm{gold.msi5}_j + \gamma_{037} \,\mathrm{intel.stimulationM}_j \\ & + \gamma_{038} \,\mathrm{mind.wanderingM}_j + \gamma_{039} \,\mathrm{motor.synchronizationM}_j \\ & + \gamma_{040} \,\mathrm{updating.musical.knowledgeM}_j + \gamma_{041} \,\mathrm{killing.timeM}_j \\ & + U_{0j} \end{aligned} \tag{2}$$

Where Y_{ij} denotes the expected musical characteristic selected by person j at situation i and β_{0j} represents a participant-specific intercept. This intercept is modeled following the second equation including all person-related variables. Within-subject effects are represented by the beta coefficients (β_1–β_{25}) and γ_{01}–γ_{041} represent between-subject effects. Capital letter C denotes within-subject centered variables and M denotes aggregated variables at the person level. The terms R_{ij} and U_j denote residuals at Levels 1 and 2.

For the categorical variables “activity” and “presence.of.others”, we used the group Lasso estimator as implemented in the glmmLasso package (Groll, 2017). This group Lasso estimator treats all categories (i.e., dummy variables) of a categorical variable as belonging together and therefore either includes all categories or excludes all categories pertaining to a categorical variable (for details see Groll & Tutz, 2014; Meier, Van De Geer, Sara, & Bühlmann, 2008; Yuan & Lin, 2006). *P*-values of non-zero coefficients were estimated by Fisher scoring re-estimation as implemented in glmmLasso (Groll, 2017).

To obtain an overview of the holistic mediation analysis, we calculated a consistency indicator I_F including the number of direct associations for each step of analysis. I_F was calculated as

$$I_F = \frac{\sum_1^i s_i}{m * i} \tag{3}$$

Where s_i is the amount of direct effects of variable s across the m models of the respective step (i.e., eight for musical characteristics during step A, B, D and five for functions of music listening during step C) and i denotes the number of variables showing direct effects on at least one of the eight outcome variables of step A. For steps B and C, only those variables were considered which already revealed a direct effect in step A (following the logic of a mediation analysis that a direct effect of y on x is mandatory). Given that the percentile-Lasso selects the most important variables, this indicator should decrease if variables selected during step A were not selected during step D. This decrease would indicate the presence of full mediations.

While these steps provided a holistic overview of all variables and effects involved in music selection, they do not directly provide estimates of direct and indirect effects of person- and situation-related variables on music-selection behavior via functions of music listening. Based on the results of the analysis described above, we constructed and tested mediation models for each outcome using multilevel structural equation modeling (MSEM; Preacher, Zyphur, & Zhang, 2010). We selected all person- and situation-related variables of steps A and C that showed significant and robust direct effects on music selection as indicated by the percentile-Lasso method. From this set, we then selected those variables that also showed a significant and robust direct effect on the proposed mediating variable (i.e., functions of music listening as indicated by step B). As mentioned earlier, we used a group Lasso estimator that either includes the complete set of dummy variables pertaining to one categorical variable or excludes them all. However, our aim was to keep models as parsimonious as possible. Therefore, we selected single significant dummy variables, but not the full set. Based on these selection criteria, we built one multilevel structural equation model for each of the eight musical characteristics.

To explore individual differences in associations between predictor variables and music-selection behavior, we re-estimated models based on step D using the lme4 package (Bates, Mächler, Bolker, & Walker, 2015) and included random slopes for all situational variables that had shown significant associations during the re-estimation step of the glmmLasso package. Significance of these random parameters was tested by likelihood ratio tests using the lmerTest package (Kuznetsova, Brockhoff, & Christensen, 2015).

All statistical analyses except the MSEM were performed within the development environment R-Studio (RStudio Team, 2015) of the software R.3.0.2 (R Core Team, 2015). MSEM mediation analyses were calculated using the software Mplus (Muthén & Muthén, 1998-2017).

3.3.3 Results

3.3.3.1 Compliance Rate

Of the 15,708 random triggers sent during the study, 117 (0.7%) were dismissed, 2,446 (15.6%) were ignored, and 62 (0.4%) were answered but not finished. This results in an overall compliance rate of 83% (13,083 out of 15,708 cases). Participants additionally reported 542 music listening situations by pressing the event button; 23 of those (2.7%) were incomplete.

3.3.3.2 Descriptive Statistics

Participants reported 3,564 music-listening situations. In 523 situations, participants did not choose to listen to music; in 25 situations, participants reported listening to music in a concert; in 28 situations, participants were listening to music in a club; and in 676 situations, they reported not having any control over the music. Of the 2,674 music-listening situations considered for the present analysis, 2,202 were based on random triggers and 472 were reported voluntarily by pressing the event button. Participants on average reported 22.5 (SD = 17.6) music-listening situations throughout the 10 days of the study. On average, participants reported 3 (SD = 2.3) listening situations per day. Participants reported the following frequencies of main activities while listening to music: being on the move (518; 19%), working & studying (476; 18%), pure music listening (476; 18%), household activity (328; 12%), other activity (230; 9%), social activity (170; 6%), relaxing & falling asleep (147; 5%), personal hygiene (132; 5%), exercise (68; 3%), coping with emotions (50; 2%), making music (50; 2%), and party (17; 1%).

3.3.3.3 Variance Components

The ICC indicates the relative amount of variance in the outcome variable attributable to person-related and situational differences. The ICC for the five dimensions of functions of music listening were: .48 for intellectual stimulation, .42 for mind wandering & emotional involvement, .40 for motor synchronization & enhanced well-being, .42 for updating one's musical knowledge, and .51 for killing time & overcoming loneliness. Across the five dimensions, on average 44% of the variance of functions of music listening was attributable to between-person differences, whereas 56% were attributable to within-person differences between situations. The ICC for the eight musical characteristics were .10 for *calming–exciting*, .10 for *slow–fast*, .17 for *sad–happy*, .22 for *less melodic–very melodic*, .24 for *less rhythmic–very rhythmic*, .16 for *simple–complex*, .08 for *peaceful–aggressive*, and .22 for *less intense–very intense*. Across all characteristics, between-person differences on average accounted for 16% of variance, whereas within-person differences between situations accounted for 84% of variance. This means that music selection was influenced largely by situational factors. In contrast, reported functions of music showed higher between-person variance, but were still outweighed by within-subject variability.

3.3.3.4 Most Important Predictors of Music Selection

Models resulting from the analysis of steps A to C are presented in the Appendix II, and the models of step D—representing the most comprehensive models—are shown in Table 1. Modeling results revealed that time (time of day, weekday vs. weekend) strongly contributed to the prediction of functions of music listening (step C), but played a minor role in the prediction of music selection (steps A and D). A closer inspection of the comprehensive models including all potential predictors (step D) shows that situation-specific arousal, degree of attention, and functions of music

Table 1. Fixed Effects Estimates (Top) and Standard Deviations of Random Parameters (Bottom) for Models of the Predictors of Music Selection. Analysis step D (see text for details)

Parameter	calming – exciting	slow – fast	sad – happy	less melodic – very melodic	less rhythmic – very rhythmic	simple – complex	peaceful – aggressive	less intense – very intense
				Fixed Effects				
Intercept	4.15 (0.06)***	4.11 (0.06)***	2.45 (0.05)***	4.93 (0.06)***	4.58 (0.07)***	4.00 (0.06)***	3.26 (0.05)***	3.53 (0.06)***
Level 1 (situational)								
Time			0.03 (0.02)					
Time²			-0.00 (0.00)					
Weekend								
Mood								
Valence			0.14 (0.02)***					
Arousal	0.11 (0.01)***	0.05 (0.01)***					0.06 (.01)***	0.04 (0.02)*
Importance of mood			0.02 (0.02)					0.02 (0.02)
Attention	0.14 (0.02)***	0.07 (0.02)***	-0.04 (0.02)*				0.08 (.02)***	0.14 (0.02)***
Activity[a]								
Pure music listening			-0.18 (0.06)**					0.07 (0.06)
Housework			-0.12 (0.07)					0.13 (0.07)*
Working & studying			-0.17 (0.07)*					0.03 (0.07)
Coping with emotions			-0.53 (0.16)***					-0.03 (0.15)
Exercise			-0.68 (0.14)***					0.16 (0.14)
Social activity			-0.11 (0.10)					0.12 (0.10)
Party			-0.70 (0.26)*					-0.29 (0.26)
Making Music			0.15 (0.17)					-0.35 (0.17)*
Relaxing & falling asleep			-0.06 (0.11)					-0.19 (0.11)
Personal hygiene			-0.15 (0.12)					0.03 (0.11)
Other activities			-0.10 (0.12)					0.17 (0.12)
Presence of others[b]								
Others present & no interaction			-0.06 (0.06)				0.05 (0.05)	
Others present & interaction			0.03 (0.07)				-0.25 (0.06)***	
Functions of music listenning								
Intellectual stimulation	-0.23 (0.02)***	-0.23 (0.02)***	-0.19 (0.02)***	0.20 (0.02)***		0.36 (0.02)***	-0.15 (0.02)***	0.24 (0.02)***
Mind wandering & emotional involvement	-0.08 (0.02)***	-0.10 (0.02)***		0.12 (0.02)***			-0.14 (0.02)***	0.12 (0.02)***
Motor synchronization & enhanced well-being	0.52 (0.02)***	0.47 (0.02)***	0.44 (0.02)***	-0.06 (0.02)**	0.33 (0.02)***		0.32 (0.02)***	0.04 (0.02)*
Updating ones musical knowledge				-0.09 (0.02)***				-0.08 (0.02)***
Killing time & overcoming loneliness			-0.05 (0.02)*				-0.12 (0.02)***	-0.06 (0.02)*

(continued)

Table 1. (continued)

Parameter	calming – exciting	slow – fast	sad – happy	less melodic – very melodic	less rhythmic – very rhythmic	simple – complex	peaceful – aggressive	less intense – very intense
				Fixed Effects				
Level 2 (person-related)								
Mood								
Valence			0.22 (0.06)***					
Presence of others[b]								
Others present & no interaction								0.62 (0.26)*
Others present & interaction								0.09 (0.34)
Intensity of music preference								
Musical taste								
Rock & Metal								0.02 (0.04)
Functions of music listenning								
Intellectual stimulation			-0.20 (0.06)**					0.21 (0.07)**
Mind wandering & emotional involvement			-0.08 (0.06)					0.20 (0.06)**
Motor synchronization & enhanced well-being			0.43 (0.06)***					
Updating ones musical knowledge								-0.23 (0.07)**
Killing time & overcoming loneliness								
				Random parameters				
Level 2 (*SD*)								
Intercept/intercept	0.64***	0.54***	0.46***	0.64***	0.76***	0.58***	0.50***	0.53***

Note. Standard error in parentheses. SD = standard deviation.

Based on a total of 2674 daily life assessment from N = 119 participants. The table only includes predictors that at least have been selected in one of the eight models. For a full list of included variables in the selection process of the percentile-Lasso see equations 1 and 2.

[a] activity comprised 12 categories, reference category: being on the move. [b] Presence of others comprised 3 categories, reference category: alone.

* $p < .05$. ** $p < .01$. *** $p < .001$.

listening proved to be most important in the prediction of music selected in a specific situation. The theory-based assumption (cf. Figure 1) that functions of music listening play a significant role in music selection was supported by the observation that almost all direct effects that were detected during step C were also selected when all potential covariates were included in the model during step D, while regression coefficients remained virtually identical. Furthermore, the percentile-Lasso almost exclusively selected situational (Level 1) predictors of music-selection behavior, whereas only very few person-related (Level 2) variables were selected, namely a few aggregated mood and function scores. None of the personality traits or musical sophistication scores contributed to the prediction of music selection. Although momentary activity contributed substantially to the prediction of functions of music listening during step B (activity was included in four out of five models) and was also selected in four out of eight models during step A, it was only of marginal importance during step D as it was only included in two out of eight models. This clearly indicates the potential mediating role of functions of music listening in the association of person- and situation-related variables with music selection.

3.3.3.5 *Mediation Analysis*

The mediation hypothesis was further supported by the consistency indicator I_F shown in Figure 2. The decrease of I_F from steps A to D clearly indicated that some of the variables selected in step A were no longer selected in step D in which functions of music listening were included as covariates. This exclusion of direct effects in the presence of potential mediators can be interpreted as full mediations.

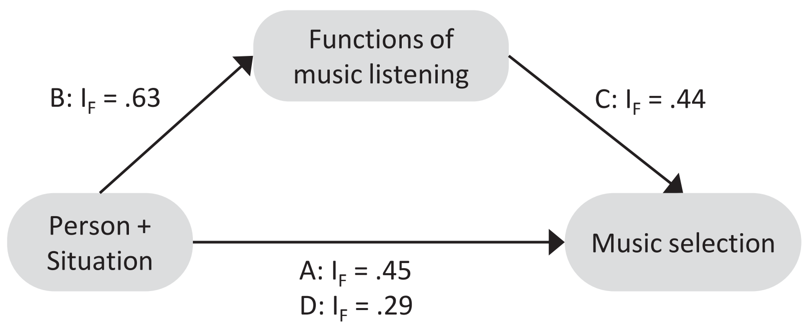

Figure 2. Summary of holistic mediation analysis using the percentile-Lasso. I_F is a consistency indicator summarising all included person and situation predictors across all respective models for each step of analysis A–D (see text for details).

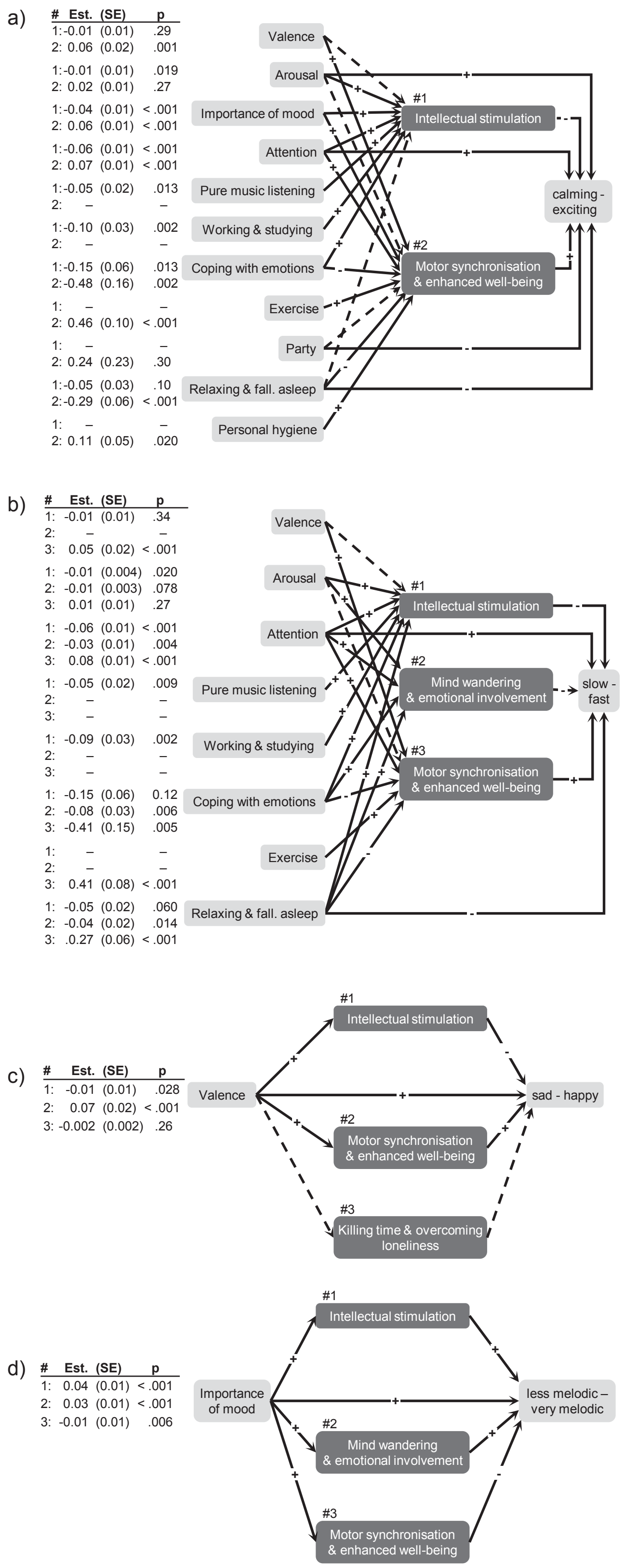

Figure 3. Multilevel mediation models for musical characteristics selected. a)–g) represent 1-1-1 mediations, h) shows 1-1-1 and 2-2-2 mediations. Variables included in the analyses where selected by the percentile-Lasso (see text for details). Plus and minus signs indicate direction of effects. Solid lines represent significant effects and dashed lines represent non significant effects. Direct effect parameters and tests from mediation models are shown left to each subfigure.

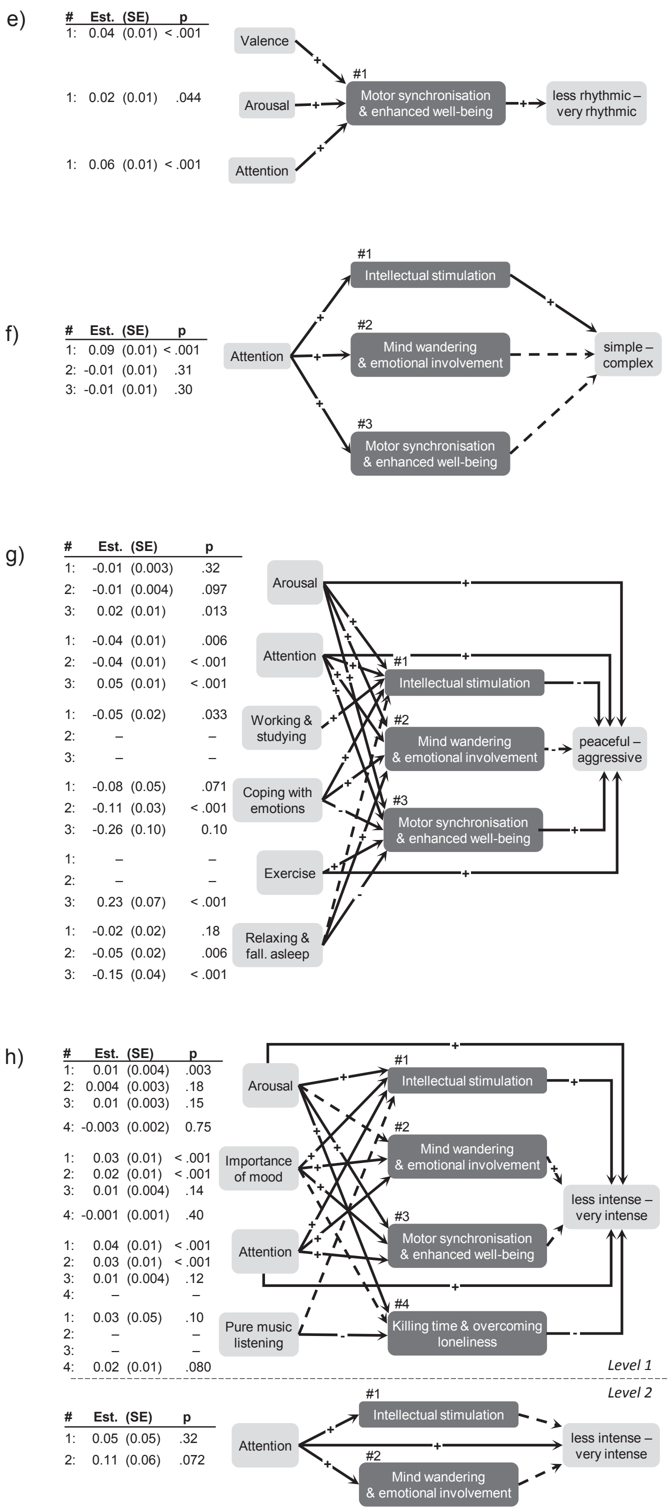

Figure 3. (continued)

Figure 3 depicts all mediation models including indirect effects (see Appendix II for detailed model summaries including coefficients of all effects). The results of these analyses revealed a similar pattern seen above, but provided further insights, particularly with regard to direct effect tests and residual paths. For example, when people reported to be in a positive mood (valence), felt higher arousal, and payed higher attention to the music compared with their individual average, they tended to listen because they could move to the music and feel fitter. This mediating functional state was in turn associated with a higher tendency to listen to rhythmic music (Figure 3, Model e). None of the three variables in this model showed a significant residual direct effect on the selection of rhythmic music, but all indirect effects were statistically significant. In another mediation model, the model for predicting selection of *sad–happy* music (Figure 3, Model c) revealed detailed findings on the broad effects of valence at the moment of the decision to listen to music. The model included an indirect positive effect of valence on happy music via motor synchronization and enhanced well-being, which was also found for choosing rhythmic (Model e), exciting (Model a), and fast music (Model b). In addition, there was a residual direct positive effect of valence on the selection of happy music, which reflects mood congruent selection of happy music. Moreover, the significant indirect path via intellectual stimulation demonstrates that people were more likely to listen to music for intellectual stimulation when they were in a positive mood, but tended to select *sad* music in that case. Such differentiated insights in specific associations including opposing directions within a mediation path were found for several models (Models a, b, c, d, and h). The mediation paths found in this study highlight both the general importance and the role of functions of music listening as a mediator in music-selection behavior. Overall, 52 (69%) of the 72 indirect effects tested throughout the eight models were significant (see Table 2).

3.3.3.6 Individual Differences of Situational Effects on Music Selection

Table 3 shows the re-estimation of the models derived from step D including random slopes for those predictors that yielded significant fixed effects in the percentile-Lasso model output. Many of the random parameters revealed significant individual variability around the overall mean effect. This variability was found consistently across all of the eight models of music-selection behavior. Overall, 24 (60%) of the 40

Table 2. Number of significant indirect effects of MSEM mediation analyses.

Outcome	Number of estimated indirect effects	Number of significant indirect effects	Percentage of significant indirect effects
calming–exciting	17	13	76%
slow–fast	17	13	76%
sad–happy	3	2	67%
less melodic–very melodic	3	3	100%
less rhythmic–very rhythmic	3	3	100%
simple–complex	3	1	33%
peaceful–aggressive	14	11	79%
less intense–very intense	15	6	40%
Sum	75	52	69%

random parameters of this analysis step were statistically significant. Particularly, the three functions of music listening intellectual stimulation, mind wandering & emotional involvement, and motor synchronization & enhanced well-being consistently showed individual variability in their association with music-selection behavior. Estimations of fixed effects were only affected marginally by the inclusion of random effects, and almost all fixed effects remained significant. This indicates that general trends can be detected reliably, but some individuals deviate from this overall trend. Such individual deviations from overall trends offer the opportunity to investigate person-related moderators.

3.3.3.7 Comparison of Results with Greb et al. (2018)

As we largely measured the same variables and used the same statistical-learning method for data analysis and variable selection (percentile-Lasso) as in an earlier study (Greb et al., 2018), we had the opportunity to compare results between two studies that differ in their participant samples and assessment methods (retrospective online survey vs. momentary assessments in daily life). Table 4 shows comparisons of variance components and fixed effects consistently selected in both studies. ICC values were virtually identical for four of the outcome variables but deviated for *simple–complex* and *peaceful–aggressive*. Exclusively situational (i.e., within-subject centered) predictors were congruently selected across both studies. For the functions of music listening, intellectual stimulation and motor synchronization & enhanced well-being, results were most consistent. For example, when people reported listening to music for intellectual stimulation, they tended to select slower, more melodic, less happy, more peaceful, and more complex music in both studies. However, even though all effects

Table 3. Fixed Effects Estimates (Top) and Standard Deviations of Random Parameters (Bottom) for Models of the Predictors of Music Selection. Model Including Random Slopes.

Parameter	calming–exciting	slow–fast	sad–happy	less melodic–very melodic	less rhythmic–very rhythmic	simple–complex	peaceful–aggressive	less intense–very intense
				Fixed Effects				
Intercept	4.15 (0.06)***	4.12 (0.05)***	2.47 (0.36)***	4.93 (0.06)***	4.58 (0.07)***	4.00 (0.06)***	3.27 (0.05)***	3.53 (0.27)***
Level 1 (situational)								
Time			0.02 (0.02)					
$Time^2$			-0.001 (0.001)					
Weekend								
Mood								
Valence			0.12 (0.02)***					
Arousal	0.11 (0.02)***	0.04 (0.02)					0.06 (0.02)**	0.04 (0.02)*
Importance of mood			0.01 (0.02)					0.01 (0.02)
Attention	0.14 (0.03)***	0.07 (0.02)**	-0.03 (0.02)				0.07 (0.03)**	0.14 (0.02)***
Activity[a]								
Pure music listening			-0.21 (0.10)*					0.05 (0.07)
Housework			-0.19 (0.10)*					0.09 (0.09)
Working & studying			-0.23 (0.10)*					0.01 (0.08)
Coping with emotions			-0.59 (0.22)*					0.01 (0.17)
Exercise			-0.71 (0.17)***					0.13 (0.15)
Social activity			-0.15 (0.11)					0.13 (0.10)
Party			-0.60 (0.33)					-0.47 (0.29)
Making Music			-0.10 (0.21)					-0.50 (0.22)*
Relaxing & falling asleep			-0.10 (0.12)					-0.16 (0.10)
Personal hygiene			-0.16 (0.13)					-0.03 (0.11)
Other activities			-0.12 (0.11)					0.11 (0.09)
Presence of others[b]								
Others present & no interaction			-0.09 (0.07)				0.04 (0.07)	
Others present & interaction			-0.0005 (0.8)				-0.21 (0.08)*	
Functions of music listenning								
Intellectual stimulation	-0.21 (0.04)***	-0.22 (0.04)***	-0.16 (0.04)***	0.21 (0.04)***		0.33 (0.04)***	-0.12 (0.04)**	0.24 (0.04)***
Mind wandering & emotional involvement	-0.07 (0.03)*	-0.09 (0.03)**		0.12 (0.02)***			-0.14 (0.03)***	0.13 (0.03)***
Motor synchronization & enhanced well-being	0.52 (0.04)***	0.48 (0.03)***	0.44 (0.03)***	-0.04 (0.03)	0.34 (0.03)***		0.32 (0.04)***	0.08 (0.03)**
Updating ones musical knowledge				-0.09 (0.03)**				-0.05 (0.03)
Killing time & overcoming loneliness			-0.06 (0.03)				-0.09 (0.03)*	-0.04 (0.03)

(continued)

Table 3. (continued)

Parameter	calming–exciting	slow–fast	sad–happy	less melodic–very melodic	less rhythmic–very rhythmic	simple–complex	peaceful–aggressive	less intense–very intense
				Fixed Effects				
Level 2 (person-related)								
Mood								
Valence			0.22 (0.06)***					
Presence of others[b]								
Others present & no interaction								0.62 (0.26)*
Others present & interaction								0.09 (0.33)
Intensity of music preference								
Musical taste								
Rock & Metal								0.02 (0.04)
Functions of music listenning								
Intellectual stimulation			-0.21 (0.06)**					0.21 (0.07)**
Mind wandering & emotional involvement			-0.07 (0.06)					0.20 (0.06)**
Motor synchronization & enhanced well-being			0.43 (0.06)***					
Updating ones musical knowledge								-0.23 (0.07)**
Killing time & overcoming loneliness								
				Random parameters				
Level 2 (*SD*)								
Intercept/intercept	0.57***	0.50***	0.44***	0.63***	0.73***	0.56***	0.45***	0.53***
Valence/valence			<0.01					
Arousal/arousal	0.07	0.12*					<0.01	0.05
Attention/attention	0.17***	0.11	0.10*				0.10	0.13***
Pure music listening/pure music listening			0.34					
Household/household								0.31*
Working & studying/working & studying			0.37*					
Coping with emotions/coping with emotions			0.53					
Exercise/exercise			<0.01					
Party/party			<0.01					
Making music/making music								0.43
Others present & interaction/others present & interaction							<0.01	
Intellectual stimulation/intellectual stimulation	0.16	0.18**	0.24***	0.25***		0.28***	0.14	0.28***
Mind wandering & emotional involvement/mind wandering & emotional involvement	0.18***	0.17***		0.07			0.14**	0.12*
Updating ones musical knowledge/ updating ones musical knowledge				0.13*				0.17***
Killing time & overcoming loneliness/killing time & overcoming loneliness			0.11				0.11	<0.01

Note. Standard error in parentheses. SD = standard deviation. Based on a total of 2674 daily life assessment from N = 119 participants. The table only includes predictors that at least have been selected in one of the eight models. Predictors were selected by the percentile-Lasso (see text for details).

[a] activity comprised 12 categories, reference category: being on the move. [b] Presence of others comprised 3 categories, reference category: alone.

* $p < .05$. ** $p < .01$. *** $p < .001$.

shared the same directions, effect sizes of the current study were smaller when compared with the effects of the retrospective online study. As all effects shown in Table 4 consistently contributed to the prediction of music selection of unseen persons, these effects can be regarded as highly robust and reliable.

3.3.4 Discussion

The current study investigated music selection in daily life by using the ESM and statistical learning methods. Our first aim was to investigate to what extent person-related and situational variables influence music selection. Findings demonstrated that characteristics of music chosen in daily life were influenced largely by the situation a person resides in, with 84% of variance being attributable to situational factors. The predominance of situational influence is consistent with Greb et al. (2018) whose results revealed virtually identical ICC values for four outcome variables. For the two variables *simple–complex* and *peaceful–aggressive,* the ICC values were considerably smaller in the present study. This difference might be explained by the fact that the results of Greb et al. (2018) were based on retrospective self-reports of three listening situations collected in an online study. The two variables for which the differences occurred are probably most susceptible to response bias due to self-perception processes. For example, people perceiving themselves as highly intellectual music connoisseurs are more likely to report situations in which they listen to complex music when being asked retrospectively. As momentary assessments—the case in our ESM study—are less susceptible to such biasing factors (Schwarz, 2012), they very likely represent situational influences more accurately. In addition, the ESM study reported here reflects a much more comprehensive representation of participants' daily lives as compared with reports of just three situations. Our results concerning the ICC values of *sad–happy* and *calming–exciting* are very similar to those of Randall and Rickard (2017) who also used daily-life assessments and measured music selection via valence and arousal. In summary, the high situational variability of music-listening behavior revealed in the current study should initiate a shift from research on individual differences to situational influences and potential interactions on music-selection behavior.

Our second aim was to identify the key variables involved in music selection. Our multi-step analytic plan revealed a detailed pattern of findings for a broad set of

Table 4. Comparison of Key Indicators (Top) and Predictor Variables (Bottom) of Retrospective Online Study by Greb et al. (2018) and the Current ESM Study.

	less melodic–very melodic		less rhythmic–very rhythmic		slow–fast		sad–happy		simple–complex		peaceful–aggressive	
	RS	ESM	RS	ESM	RS	ESM	RS	ESM	RS	ESM	RS	ESM
ICC	.28	.22	.22	.24	.09	.10	.18	.17	.29	.16	.32	.09
# Predictors	1	4	1	1	11	5	7	14	13	1	10	7

Parameters	Predictors consistently selected in both studies: Estimates											
Situational predictors												
Intellectual Stimulation	0.59 (0.06)	0.20 (0.02)			-0.49 (0.07)	-0.23 (0.02)	-0.09 (0.08)	-0.19 (0.02)	0.61 (0.08)	0.36 (0.02)	-0.25 (0.07)	-0.15 (0.02)
Motor sync. & enhanced well-being			0.79 (0.05)	0.33 (0.02)	0.91 (0.06)	0.47 (0.02)	0.73 (0.07)	0.44 (0.02)			0.59 (0.07)	0.32 (0.02)
Killing time & overcoming loneliness											-0.14 (0.07)	-0.12 (0.02)
Attention					0.06 (0.03)	0.07 (0.02)	-0.03 (0.03)	-0.04 (0.02)			0.06 (0.03)	0.08 (0.02)
Valence [a]							0.21 (0.03)	0.14 (0.02)				
Arousal [a]					0.10 (0.03)	0.05 (0.01)					0.07 (0.03)	0.06 (0.01)

Note. Standard errors in parentheses. RS = Retrospective online study by Greb et al (2018). ESM = Current study using the experience sampling method. The table only includes predictors which have been selected in both studies and were measured identically.

[a] effects of valence and arousal are reported separately in Greb et al. (2018).

relevant variables. The finding that activity was important in predicting functions of music listening is consistent with previous research also revealing activity as very important in predicting listening functions or music perception in daily life (Greb et al., 2017; Krause & North, 2017b; Randall & Rickard, 2017). The insight that, when controlling for the largest possible set of covariates, situation-specific attention, arousal, and functions of music listening were most important in predicting music selection is largely in line with findings by Greb et al. (2018). Many of the direct effects that were revealed in the first steps of our analysis dropped out when controlling for functions of music listening. This supports our theoretical model proposing a mediating role of functions of music listening for the association between person- and situation-related predictor variables and music-selection behavior.

Clarifying the mediating role of functions of music listening in music selection was our third aim. Several analyses supported the mediation hypothesis. First, our consistency indicator clearly suggested several full mediations. Second, our findings from MSEM demonstrated that in many cases (69% of tested indirect effects) functions of music listening acted as mediators on the selection of music with specific characteristics. It is important to mention that the mediation processes found in our study were exclusively located on the situational level (Level 1). Momentary mood, attention, and activity largely determined why participants listened to music, and the specific functions ultimately predicted which music participants selected. We did not find any significant mediation effects on the between-subject level (Level 2). The large within-subject variance of musical characteristics selected might explain this absence of between-subject mediations. The novel findings on within-subject mediations help to understand the important role of functions of music listening in music selection that would have been neglected by an analysis strategy strictly focused on direct effects. For example, the results related to the direct effect of valence on the selection of *happy–sad* music confirm mood-congruent selection of music (Randall & Rickard, 2017; Thoma, Ryf, Mohiyeddini, Ehlert, & Nater, 2012), whereas the indirect effect via intellectual stimulation demonstrates mood-incongruent selection of music. These findings for the first time clearly differentiate the complex processes involved when people select music in daily life.

Our fourth aim was to investigate individual variations of situational effects identified in the previous analyses. Here, findings demonstrated that many associations significantly varied around the estimated mean effect. The three functions of intellectual stimulation, mind wandering & emotional involvement, and motor synchronization & enhanced well-being most consistently showed individual deviations. For example, this indicates that people generally tend to select faster, happier, less melodic, more rhythmic, more aggressive, more intense, and more exciting music to move to and enhance their well-being, but individuals do deviate from these overall trends. Hence, future research should investigate which person-related factors might explain the individual variability found here. One analysis strategy might be to add cross-level interaction parameters. Such an analysis could focus on two associations outlined by our theoretical model (Figure 1): individual variability in the association between situational variables and functions of music listening and music-selection behavior. In addition, moderated mediation models could be used to check whether person-related variables are capable of explaining individual variation in the mediation of the association between predictors and music-selection behavior by functions of music listening. This approach would also provide an opportunity to integrate person-related variables more precisely into theoretical models of music-selection behavior. It might well be the case that very few direct effects of person-related variables on music selection exist, and that person-related variables rather act as moderators. Once more, this would suggest a shift from exclusively investigating individual differences to interaction effects between situational and person-related variables on music-listening behavior.

Lastly, we aimed to compare the results of this daily-life study to those of a recent study on music selection that was very similar in terms of theoretical background and statistical analysis but analyzed data from a retrospective online survey (Greb et al, 2018). Besides the virtual identical ICC values discussed above, we found numerous effects going in the same direction. Exclusively situational predictors were selected congruently across both studies. Consensus was greatest for intellectual stimulation and motor synchronization & enhanced well-being. For example, findings consistently indicated that people tend to select more melodic, less fast, less happy, less aggressive, and more complex music when they listen to music for intellectual stimulation. Although some effect sizes were largely identical, others differed in size with effects of this study being smaller than those obtained through the online study. This difference might be due to memory biases and a tendency to report stereotypically in retrospective reports (Holmberg & Homes, 2012). The effects found across both studies can be regarded as highly robust and reliable. As in both studies, models were optimized to make predictions on unseen participants, these effects can be used to guide stimulus selection for experimental research investigating specific functions or effects of music listening. In addition, the similarity of results highlights the power of using statistical learning methods, the percentile-Lasso in this case, for reliable variable selection. Despite broad congruency between the two studies, a number of differences are evident that mainly concern the selection of person-related predictors. Greb et al. (2018) found person-related effects on selecting *slow–fast*, *simple–complex*, and *peaceful–aggressive* music, whereas the present daily-life study revealed person-related effects for *sad–happy* and *less intense–very intense* (which was not measured in the retrospective study). In the online study, musical taste factors were found to be important predictors—being selected in three out of six models—but in the current study, only one musical taste factor was selected in one out of eight models. As already discussed above, *simple–complex* and *peaceful–aggressive* showed different ICC values across both studies with values of the online study being considerably larger. This further supports the point made above that participants in the online study might have reported stereotypical situations that match their attitudes and beliefs, such as musical taste, whereas in the ESM study, the behavioral report was much less biased. Hence, the current findings do not support the idea that musical taste is associated with the selection of certain musical characteristics.

None of the Big Five personality traits was selected as a predictor of music-selection behavior in the current study. This is consistent with Schäfer and Mehlhorn (2017) who showed that personality traits cannot substantially account for differences between individuals in musical taste and preferences. We believe that the Big Five personality traits might be too broad to predict such a fine-grained behavior as music selection. Future research might investigate if facets of Big Five personality traits, which represent specific and unique aspects underlying the broad personality traits, are better predictors of music selection.

Our study includes several notable limitations. First, music selection was measured based on subjectively perceived musical characteristics based on a particular conceptualization of music-selection behavior. Convergence with objective measures, such as musical features, obtained by music information retrieval methods would provide interesting comparative data for some of the current findings. In particular, this comparison could show if the perception of musical characteristics is congruent with objective characteristics or if subjective perception is influenced by the situation as well. Music-selection behavior could also be conceptualized via musical styles selected, which might lead to different relations of person-related and situational influences found here. A style-based conceptualization would help to clarify if people predominantly select and listen to their favorite styles of music but adapt their concrete musical choices (i.e., characteristics of the music) within their favorite styles to the situation they reside in. Hence, future research should try to model these different conceptualizations simultaneously to best reflect interdependencies and isolate effects of individual variables in the context of the complex entirety of potentially relevant variables.

Second, not accounting for covariations of outcome variables constitutes another limitation. This restriction is based on the fact that, to the best of our knowledge, no package or software solution exists that is able to perform a Lasso regression in a multivariate multilevel model framework. It is important to note that our results of modeling predictors of different musical characteristics are based on independent models. Therefore, it is possible that a single multivariate model could lead to slightly different results.

Lastly, our findings are based on a specific sample of young people who frequently listen to music and are familiar with digital technologies. These digital natives grew up with technologies that enable situation-specific music selection. Hence, our findings should be replicated using a broader sample also including infrequent music listeners with greater age variability. Nevertheless, the fact that we found a large overlap of effects between the present and an earlier study that did not focus on frequent music listeners highlights the reliability of our results.

The current study investigated music-selection behavior in daily life from a comprehensive perspective, using representative and unbiased momentary samples from participants' everyday life and innovative statistical learning procedures suitable for this endeavor. We demonstrated that situational factors mainly drive music selection and identified detailed patterns of variables contributing to music-selection behavior. We also showed for the first time that functions of music listening act as mediators between the situation and music-selection behavior. Our study therefore contributes to the understanding of music-selection behavior, in particular how situational characteristics influence people's motives to listen to a particular kind of music and actual musical choices. These findings emphasize the importance of accounting for situational influences in music psychological research, and could also be used to enhance music recommendation systems.

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4 General Discussion

Music listening constitutes an important part of people's daily lives. Technological developments now allow people to individually select and listen to music in almost any situation. In contrast to the widespread use of these technologies, relatively little is known about the underlying processes of people selecting and listening music in daily life. The majority of research on music listening has exclusively focused on individual differences while largely ignoring situational factors. On the other hand, the few investigations that have focused on situational factors have neglected to incorporate individual differences in their research and theories. Therefore, the present dissertation addressed this gap by simultaneously investigating person-related and situational factors influencing music listening in daily life. To date, only two theoretical models by Hargreaves et al. (2005) and Randall and Rickard (2017) exist that integrate the large number of bivariate associations identified by previous research. While the reciprocal feedback model of musical response by Hargreaves et al. (2005) treats the listener as an entity that passively responds to music, Randall and Rickard (2017) focus on music listening via headphones as well as explaining emotional outcomes of listening to music. Thus, the research reported here was guided by the process model of music selection proposed by the author (Figure 2.3). This model suggests that functions of music listening play a central role in the selection of music. While the functions can be influenced by situational and person-related variables, they are suggested to act as a mediator between person, situation and music selection. Guided by this model, the current dissertation aimed to answer four major questions, and the findings of the empirical investigations presented in the previous chapter that relate to those questions will be discussed here. Subsequently, the enhancement of the empirically grounded process model of music selection is presented, and limitations, including suggestions for future research, will be outlined.

The first question was concerned with the relative influence of person and situation on the functions of music listening and on music-selection behavior in daily life. While the first paper addressed this question with regard to the functions of music listening, the second paper focused on music selection. The third paper provided answers to both questions based on more reliable daily-life data. Overall, findings indicated that music listening in everyday life is predominantly attributable to the situation. While characteristics of the selected music were revealed to be almost entirely determined within the situation, functions of music listening showed greater variation between individuals. This indicates that people differ in why they listen to music but the concrete selection of music is shaped by the situation. This suggests that even music with different musical characteristics is able to some extent to serve the same listening functions. The predominance of situational influences on different aspects of music listening behavior is largely in line with Randall and Rickard (2017), who found emotional responses to music to be almost entirely determined by the situation. Nevertheless, the empirical investigations presented here were the first that quantified the relative influence of person and situation on a broad set of music listening variables. Although Vladimir Konečni stated in 1982 that the vast majority of research treated aesthetic preference and choice "as if they were independent of the context in which people enjoy aesthetic stimuli in daily life" (Konečni, 1982, p. 498), still very few attempts exist that integrate situational factors. The great situational variability of music-listening behavior revealed by the empirical investigations of the current dissertation therefore highlights the need of future research to better account for situational influences by theoretical models and research design. Notably, laboratory research on specific effects of music should become aware of the fact that people use certain listening functions under highly specific situational constraints. In addition, research on listening typologies following the assumption that a person is a certain kind of listener who continuously uses the same listening functions should consider that people strongly adapt their listening behavior to specific situations. To better reflect this fact, typology research could benefit from using daily-life research methods, which would also create a different conceptualization of listener typologies. Instead of assuming that people always listen to music in the same way, listener typologies could be best conceived as general tendencies across different situations (i.e., mean values of listening functions across several situations). This conceptualization would match the synthesis approach of research on personality traits as proposed by Fleeson and Noftle (2008).

The second major question was concerned with the identification of the most important factors influencing music listening. Here, findings of all three papers revealed detailed patterns of variables being associated with the functions of music listening and the selection of music. A major finding across the three papers was that functions of music listening and music selection were partly influenced by different variables. For functions of music listening, current activity, attention, mood, and time were consistently revealed to be important. In contrast, music selection was mainly influenced by situation-specific functions of music listening, attention and mood. In particular, the functions of intellectual stimulation and motor synchronization and enhanced well-being showed great consistency across both studies. Findings with regard to person-related variables, however, were inconsistent. Although the online study revealed several associations of person-related variables with both functions of music listening and music selection, the ESM study did not confirm these associations, actually finding fewer associations. These differences were assumed to be due to memory biases and a tendency to report stereotypically in retrospective reports as was the case in the online study. Nevertheless, the consistency of findings of situational influences on music-selection behavior indicate general principles underlying the selection of music in daily life. These findings could be used for stimulus selection of research investigating certain effects of music and could also be used to enhance music recommendation systems.

The third major question was related to the consistency of situational effects across individuals. Here findings of the first and third paper indicated that individuals significantly deviated from the situational effects that were estimated across all participants. These deviations were consistently found across all functions of music listening and all music characteristics measured in the current work. The absence of person-related variables consistently predicting listening functions or music-selection behavior suggests the possibility that very few direct associations between person-related variables and music listening exist. The individual deviations indicate that person-related variables act as moderators. This highlights not only the need for future research to consider interaction effects of person and situation, but also suggests a shift in music listening research from focusing on individual differences to interaction effects between situational and person-related variables.

Finally, the fourth question was concerned with the potential mediating role of functions of music listening between person, situation and music-selection behavior. Findings presented in the third paper clearly indicated for the first time that functions of listening in many cases act as a mediator between the situation and the selection of music. In particular, momentary mood, attention, and activity largely determined why individuals listened to music, while listening functions subsequently predicted what music participants selected. Additionally, some direct effects of situational variables were significant. Any indirect mediation paths were found between person-related variables and music selection. The detailed mediation analyses disentangled some of the complex processes involved when people select music in everyday life. For example, the analyses revealed several patterns that explained mood-congruent and mood-incongruent selection of music. As the influence of current mood on musical choices is an ongoing debate in music psychology (for an overview see Hargreaves & North, 2010), these results provide novel insights that clarify the complexity of processes underlying these choices. In addition, these analyses revealed situation-specific functions of music listening as the most important variables predicting music selection. This highlights the need to incorporate listening functions into theoretical models that aim to explain music listening in daily life. In addition, these insights could easily be adapted by music streaming services via integrating functions of music listening in recommendation systems.

Overall, the empirical work presented here revealed several novel details about people selecting and listening to music in everyday life. Figure 4.1 summarizes the results discussed above and presents the empirically derived and enhanced process model guiding the present research, including suggestions for future research. In particular, the model suggests opportunities to integrate cross-level interactions at several stages, which refer to the significant individual deviations of situational effects discussed above. Hence, interactions between person and situation should be considered when investigating functions of music listening and music-selection behavior. In addition, person-related variables are assumed to influence the association between situation-specific functions of music listening and music-selection behavior. This model was extended by effects and responses of music listening to better reflect the entire listening process and enhance the compatibility with the broader framework of the reciprocal feedback model of musical response by Hargreaves et al. (2005). These effects and responses are assumed to affect the situation (e.g., by creating another atmosphere) and the person (e.g., by changing a person's musical taste). Compared to the reciprocal feedback model of musical response, this model details the processes involved when people actively chose music as well as verifiable associations.

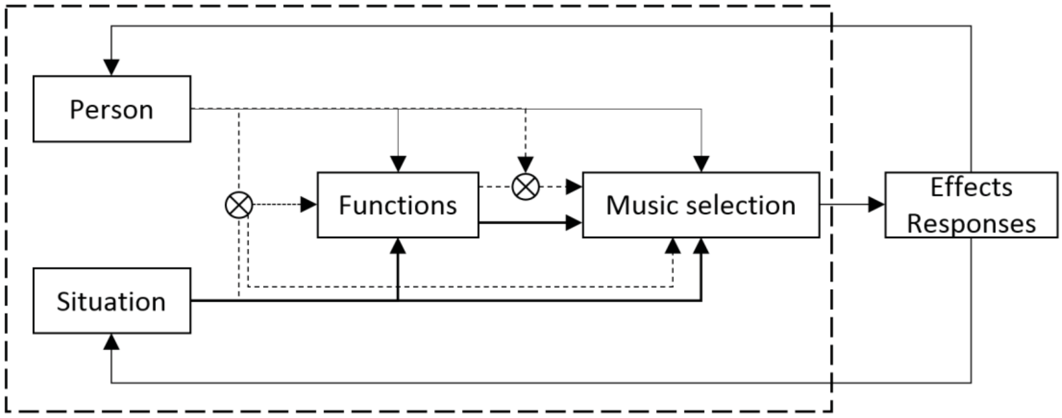

Figure 4.1. Empirically derived process model of music selection, including suggestions for future research. The area inside the dashed rectangle marks the part of the model that was empirically investigated, while the area outside of the rectangle contains suggestions for future research. Thick lines indicate strong associations, while thin lines represent weak associations revealed by the present findings. Dashed lines are suggestions for future research derived from the current findings.

Furthermore, the previously discussed findings of the current dissertation demonstrated several benefits of experience sampling data and multilevel modeling. These models enable the estimation of general trends between and within individuals (i.e., fixed effects) while also allowing the inclusion of individual variability (i.e., random effects). This allows the investigation of general trends and individual deviations from those trends. Therefore, to a certain extent these models provide an opportunity to address nomothetic and ideographic research interests simultaneously, which for some time has been a subject of debate in psychology (Bem, 1983; Conner, Tennen, Fleeson, & Barrett, 2009; Hommel & Colzato, 2017).

Although several limitations of the present research were already discussed within the single papers of Chapter 2, the major limitations and their implications for future research will be briefly outlined here.

In the empirical work presented, music was measured based on subjectively perceived musical characteristics. This conceptualization was chosen as people select music based on their individual perceptions. As these subjective perceptions might vary between individuals, future research should additionally include objective measures (e.g., tempo) obtained by music information retrieval techniques. This would allow for controlling for individual differences in subjective perceptions of musical characteristics. In addition, music selection could also be measured via style tags such as jazz, rock, or hip-hop. For those measurements, different relations of situational and person-related influences are expected. Although musical taste did not play a major role in predicting selected musical characteristics in the current work, it might be more important in predicting chosen musical styles. Individuals may predominantly select musical styles matching their musical taste and adapt their selection of music within these styles to the situation or the intended function. Hence, future research should investigate these additional conceptualizations of music-selection behavior. However, musical choices in daily life are based on subjective perceptions of music. Therefore, subjective measurements should be complemented but not replaced by the additional measures detailed above.

The empirical research presented here is based on convenience samples consisting mostly of German students. Hence, the current findings are limited in their interpretation, and future research should replicate our findings with samples from other cultures and with greater age variability. While younger people (digital natives) grew up with the possibilities of portable music listening, older people might differ in their selection behavior.

Furthermore, it is important to clarify that music-listening behavior should not be seen exclusively as a causal result of a combination of person-related and situational factors. On the one hand, some situations are normatively related to certain behaviors, listening functions, and music characteristics. For example, classical concert attendees sit still while attentively listening to music, whereas the loud and rhythmic music in a dance club is intended to evoke movement. On the other hand, people can actively change situations to better fit their needs and goals. Due to this circularity, it becomes increasingly difficult to carve out causal relationships between all of these influencing factors.

The present dissertation investigated music listening from a comprehensive perspective motivated by the fundamental questions of who listens to what music in what situations and why. The empirical investigations presented constitute a significant step towards a better understanding of people selecting music in their daily life. The finding that the selection of music in daily life is predominately driven by situational factors suggests several shifts of research foci and concepts. However, technological developments in listening technologies will continue to change the ways in which people engage with music. Nevertheless, the findings revealed by the present dissertation provide not only a detailed picture of the status quo, but also several suggestions for future research. Moreover, the up-to-date methods applied for data collection and modelling may also be useful for investigating the future development of music-listening behavior in daily life.

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APPENDIX I QUESTIONNAIRE USED IN THE ONLINE STUDY

This Appendix contains the supplemental material that is referred to in the original publication and is available online.

Supplemental material

This supplemental material formed part of the original submission and has been peer-reviewed.

Supplement to: Greb F., Steffens J., & Schlotz W. Understanding music selection behavior via statistical learning: Using the percentile-lasso to identify the most important factors. *Music & Science.*

Questionnaire used in the online survey. Terms in squared brackets represent the variable names used throughout the paper. For categories without squared brackets, the variable name equals the category name. Questions without specific response option were answered in free response format.

Section A (Situation)

Please describe the first/ second/ third situation, you typically listen to music (e.g. with regard to the location, activity, etc.). Please do so using a concise sentence as detailed as you regard necessary. [Situation description]

Please further describe the situation by answering the following questions:

Are there others present in the situation you just described? [Presence of others]

- □ No, I am alone [Alone]
- □ Yes, I am surrounded by others but do not interact / communicate with them [Others present & no interaction]
- □ Yes, I interact or communicate with others [Others present & interaction]
- □ Unspecific [Unspecific]

Did you choose the music? [Possibility of Choice]

- □ Yes [Yes]
- □ No [No]
- □ Radio [Radio]
- □ Disco [Disco]
- □ Concert [Disco]
- □ Unspecific [Unspecific]

Where are you typically in this situation? [Location]

How is your mood at the time you decide to listen to music? [Mood]

Bad	1 – 2 – 3 – 4 – 5 – 6 – 7	Good	or □ unspecific [Valence]
Tired	1 – 2 – 3 – 4 – 5 – 6 – 7	Awake	or □ unspecific [Arousal]

How important is your mood for your decision to listen to music? [Importance of mood]

Not at all 1 – 2 – 3 – 4 – 5 – 6 – 7 Very much

At which time of day does this situation usually occur? - Multiple choice [Time of day]

- □ Early Morning
- □ Morning
- □ Noon
- □ Afternoon
- □ Evening
- □ Night

How much attention do you pay to the music in this situation? [Attention]

Little 1 – 2 – 3 – 4 – 5 – 6 – 7 A lot or □ unspecific

How much do you usually like the music in this situation? [Liking]

I do not like it so much 1 – 2 – 3 – 4 – 5 – 6 – 7 I like it a lot □ unspecific

How often does the situation just described occur in your everyday life? Single forced choice [Frequency]

- □ 1 – 4 times per year
- □ 5 – 11 times per weak
- □ 1 – 3 times per month
- □ 1 – 3 times per week
- □ 4 – 7 times per week
- □ More than once a day

Section B (Music)

Which musical characteristics does the music you usually listen to have in the situation just described?

Calming	1 – 2 – 3 – 4 – 5 – 6 – 7	Exciting	or □ unspecific
Less melodic	1 – 2 – 3 – 4 – 5 – 6 – 7	Very melodic	or □ unspecific
Less rhythmic	1 – 2 – 3 – 4 – 5 – 6 – 7	Very rhythmic	or □ unspecific
Slow	1 – 2 – 3 – 4 – 5 – 6 – 7	Fast	or □ unspecific
Sad	1 – 2 – 3 – 4 – 5 – 6 – 7	Happy	or □ unspecific
Known	1 – 2 – 3 – 4 – 5 – 6 – 7	Unknown	or □ unspecific
Simple	1 – 2 – 3 – 4 – 5 – 6 – 7	Complex	or □ unspecific
Peaceful	1 – 2 – 3 – 4 – 5 – 6 – 7	Aggressive	or □ unspecific

Section C (Functions of music listening)

Why do you listen to music in the situation described?

I listen to music because…

it helps me learn about myself. (I)

It gives me intellectual stimulation. (I)

It reduces my stress. (III)

It makes me feel less lonely. (V)

It puts fantastic images or stories in my head. (II)

It lets me forget the world around me. (II)

It mirrors my feelings and moods. (II)

It gives me a way to let off steam. (III)

It reminds me of certain periods of my life or past experiences. (II)

It gives me goose bumps. (II)

It addresses my sense of aesthetics. (I)

It helps me understand the world better. (II)

It makes me feel connected to all people who like the same kind of music. (IV)

I am interested in the musicians or bands. (I)

I want to inform myself about hits and trends. (IV)

I can learn about new pieces. (IV)

It enables me to kill time. (V)

It enhances my mood. (III)

It makes me feel fitter. (III)

I can move to the music. (III)

I need it in the background while I do other things. (V)

I can sing or hum along. (III)

All above listed items where answered on the following scale:

Strongly disagree 1 – 2 – 3 – 4 – 5 – 6 – 7 Strongly agree

[Roman numerals in parentheses indicate which items belong to which factor.

Intellectual Stimulation (I), Mind Wandering & Emotional Involvement (II), Motor Synchronization & Enhanced Well-being (III), Updating One's Musical Knowledge (IV), Killing Time & Overcoming Loneliness (V).

These indicators were not part of the online study and not shown to participants. For a detailed report on the construction of the inventory see Greb, F., Schlotz, W., & Steffens, J. (2017). Personal and situational influences on the functions of music listening. *Psychology of Music*. doi:10.1177/0305735617724883.]

Section D (Person)

The following questions are not related to the three situations you just described.

Please indicate how much you like the following musical styles. All styles were measured using the following scale:

I do not like at all	I do not like	I rather do not like	Neutral	I like a bit	I like	I like very much
☐	☐	☐	☐	☐	☐	☐

Or I do not know

☐

Blues

Jazz

Funk

Soul

Reggae

Techno

EDM

House

Rap/Hip-Hop

Other cultures

Latin

World music

Classical

German “Volksmusik”

German “Schlager”

Country

Pop

Rock

Metal

For the following questions, please choose the most appropriate category. [Musical Training]

I have never been complimented for my talents as a musical performer.

I would not consider myself a musician.

Completely Disagree	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Completely Agree
☐	☐	☐	☐	☐	☐	☐

I engaged in regular, daily practice of a musical instrument (including voice) for ___ years.

□ 0 □ 1 □ 2 □ 4 □ 4-5 □ 6-9

□ 10 or more

At the peak of my interest, I practiced ___ hours per day on my primary instrument.

□ 0 □ 0.5 □ 1 □ 1.5 □ 2 □ 3-4

□ 5 or more

I have had formal training in music theory for __ years

□ 0 □ 0.5 □ 1 □ 1.5 □ 2 □ 3

□ 4-6 □ 7 or more

I have had __ years of formal training on a musical instrument (including voice) during my lifetime.

□ 0 □ 0.5 □ 1 □ 2 □ 3-5 □ 6-9

□ 10 or more

I can play ___ musical instruments

□ 0 □ 1 □ 2 □ 3 □ 4 □ 5

□ 6 or more

Please indicate how strong you agree with the following statements. Each item was rated on the following scales [Intensity of music preference]

I do not agree at all 1 – 2 – 3 – 4 – 5 – 6 – 7 I completely agree

I like music

I couldn’t live without music

I regularly visit clubs or concerts to listen to music

I just need music

I’m a passionate listener of music

I usually spend a lot of money to purchase music

Your biological gender is? [Sex]

□ Female □ Male □ Intersexual □ Transsexual □ Other

How old are you? ___ [Age]

10 Item Big Five Inventory (BFI-10) by Rammstedt, B., Kemper, C. J., Klein, M. C., Beierlein, C., & Kovaleva, A. (2013)

The questionnaire was presented in German language (available upon request)

Appendix II Supplemental Material of Paper 3

This Appendix contains the supplemental material that is referred to in the original manuscript and was submitted for publication.

Questionnaire answered on Smartphones during the 10 day course of the study (ESM Measures)

The questionnaire was presented and answered through movisensXS, Version 1.0.1 (movisens GmbH, 2015).

1. Do you currently listen to music?

- □ Yes, I currently listen to music.
- □ No, I currently do not listen to music.

Section 1 [Situation]

2. For how long you have been listening to music already? Please indicate the duration in minutes: Free response

3. Please choose your current main activity [Activity][2]:

- □ Pure music listening
- □ Housework
- □ Working / studying
- □ Coping with emotions
- □ Exercise
- □ Social activity (e.g., eating or playing with friends)
- □ Party
- □ Making music
- □ Relaxing / falling asleep
- □ Being on the move (bus/ train/ car)
- □ Personal hygiene
- □ Other (none of the activity listed is appropriate)

4. Are there currently any other persons present? [Presence of others]

- □ No, I am alone.
- □ Yes, I am surrounded by others but do not interact or communicate with them.
- □ Yes, I interact / communicate with other people.

5. Did you choose the music? [Choice]

- □ Yes
- □ No
- □ Radio
- □ Club
- □ Concert
- □ Playlist

[2] The categories were developed by Greb, Schlotz, and Steffens (2017). We included personal hygiene as an additional category based on feedback of pretesting the current study.

6. How much control do you have in what you hear? [Control]

Any control	1 – 2 – 3 – 4 – 5 – 6 – 7	Full control

7. How was your mood at the moment you decided to listen to music? [Valence]

Bad	1 – 2 – 3 – 4 – 5 – 6 – 7	Good

8. How awake did you feel at the moment you decided to listen to music? [Arousal]

Tired	1 – 2 – 3 – 4 – 5 – 6 – 7	Awake

9. How important was your mood for your decision to listen to music? [Importance of mood]

Not at all	1 – 2 – 3 – 4 – 5 – 6 – 7	Very important

10. How much attention are you paying to the music? [Attention]

Little	1 – 2 – 3 – 4 – 5 – 6 – 7	A lot

Section 2 [Music]

11. How loud is the music?

Quiet	1 – 2 – 3 – 4 – 5 – 6 – 7	Loud

12. How much do you like the music?

I like it less	1 – 2 – 3 – 4 – 5 – 6 – 7	I like it a lot

13. Please name the composer/ artist if known: Free response

14. Please name the title of the piece if known: Free response

15. Please name the musical style if known: Free response

16. Which characteristics does the music have? [Musical characteristics]

Calming	1 – 2 – 3 – 4 – 5 – 6 – 7	Exciting
Slow	1 – 2 – 3 – 4 – 5 – 6 – 7	Fast
Sad	1 – 2 – 3 – 4 – 5 – 6 – 7	Happy
Unfamiliar	1 – 2 – 3 – 4 – 5 – 6 – 7	Familiar
Less melodic	1 – 2 – 3 – 4 – 5 – 6 – 7	Very melodic
Less rhythmic	1 – 2 – 3 – 4 – 5 – 6 – 7	Very rhythmic
Simple	1 – 2 – 3 – 4 – 5 – 6 – 7	Complex
Peaceful	1 – 2 – 3 – 4 – 5 – 6 – 7	Aggressive
Less intense	1 – 2 – 3 – 4 – 5 – 6 – 7	Very intense
Instrumental	0 – 1	Vocal

Section 3 [Functions of music listening]

17. Why do you currently listen to music? [Functions of music listening]

… because it gives me intellectual stimulation. (I)
Not at all 1 – 2 – 3 – 4 – 5 – 6 – 7 Fully agree
… because it mirrors my feelings and moods. (II)
Not at all 1 – 2 – 3 – 4 – 5 – 6 – 7 Fully agree
… because it makes me feel fitter. (III)
Not at all 1 – 2 – 3 – 4 – 5 – 6 – 7 Fully agree
… because it addresses my sense of aesthetics. (I)
Not at all 1 – 2 – 3 – 4 – 5 – 6 – 7 Fully agree
…. because it puts fantastic images or stories in my head. (II)
Not at all 1 – 2 – 3 – 4 – 5 – 6 – 7 Fully agree
… because I can learn about new pieces. (IV)
Not at all 1 – 2 – 3 – 4 – 5 – 6 – 7 Fully agree
… because it enables me to kill time. (V)
Not at all 1 – 2 – 3 – 4 – 5 – 6 – 7 Fully agree
… because it helps me learn about myself. (I)
Not at all 1 – 2 – 3 – 4 – 5 – 6 – 7 Fully agree
… because it reminds me of certain periods of my life or past experiences. (II)
Not at all 1 – 2 – 3 – 4 – 5 – 6 – 7 Fully agree
… because it makes me feel connected to all people who like the same kind of music. (IV)
Not at all 1 – 2 – 3 – 4 – 5 – 6 – 7 Fully agree
… because I can move to the music. (III)
Not at all 1 – 2 – 3 – 4 – 5 – 6 – 7 Fully agree
… because I need it in the background while I do other things. (V)
Not at all 1 – 2 – 3 – 4 – 5 – 6 – 7 Fully agree
… because I want to inform myself about hits and trends. (IV)
Not at all 1 – 2 – 3 – 4 – 5 – 6 – 7 Fully agree
… because it enhances my mood (III)
Not at all 1 – 2 – 3 – 4 – 5 – 6 – 7 Fully agree
… because it makes me feel less lonely. (V)
Not at all 1 – 2 – 3 – 4 – 5 – 6 – 7 Fully agree
… because I do it out of habit. *
Not at all 1 – 2 – 3 – 4 – 5 – 6 – 7 Fully agree

[Roman numerals in parentheses indicate which items belong to which factor.
Intellectual Stimulation (I), Mind Wandering & Emotional Involvement (II), Motor Synchronization & Enhanced Well-being (III), Updating One's Musical Knowledge (IV), Killing Time & Overcoming Loneliness (V)
These indicators were not part of the study and not shown to participants. For a detailed report on the construction of the inventory see Greb, Schlotz, and Steffens (2017).
*This item was not part of the inventory and was not analyzed in the current study]

The questionnaire was originally presented in German language and is available upon request.

Model equations entered in the percentile-Lasso procedure

Step A

Level 1 equation:

$$\begin{aligned} Y_{ij} = \ & \beta_{0j} + \beta_1 \text{ time}_{ij} + \beta_2 \text{ time}_{ij}^2 + \beta_3 \text{ weekend}_{ij} + \beta_4 \text{ valenceC}_{ij} + \beta_5 \text{ arousalC}_{ij} \\ & + \beta_6 \text{ imp. of. moodC}_{ij} + \beta_7 \text{ attentionC}_{ij} + \beta_8 \text{ activity1C}_{ij} + \cdots \\ & + \beta_{18} \text{ activity11C}_{ij} + \beta_{19} \text{ presence. of. others1C}_{ij} \\ & + \beta_{20} \text{ presence. of. others2C}_{ij} + R_{ij} \end{aligned}$$

Level 2 equation:

$$\begin{aligned} \beta_{0j} = \ & \gamma_{00} + \gamma_{01} \text{ valenceM}_j + \gamma_{02} \text{ arousalM}_j + \gamma_{03} \text{ imp. of. moodM}_j + \gamma_{04} \text{ attentionM}_j \\ & + \gamma_{05} \text{ activity1M}_j + \cdots + \gamma_{015} \text{ activity11M}_j \\ & + \gamma_{016} \text{ presence. of. others1M}_j + \gamma_{017} \text{ presence. of. others2M}_j \\ & + \gamma_{018} \text{ sex}_j + \gamma_{019} \text{ age}_j + \gamma_{020} \text{ intensity. musicpreference}_j \\ & + \gamma_{021} \text{ musical. taste1}_j + \cdots + \gamma_{026} \text{ musical. taste6}_j + \gamma_{027} \text{ big5.1}_j + \cdots \\ & + \gamma_{031} \text{ big5.5}_j + \gamma_{032} \text{ gold. msi1}_j + \cdots + \gamma_{036} \text{ gold. msi5}_j + U_{0j} \end{aligned}$$

Step B

Level 1 equation:

$$\begin{aligned} Y_{ij} = \ & \beta_{0j} + \beta_1 \text{ time}_{ij} + \beta_2 \text{ time}_{ij}^2 + \beta_3 \text{ weekend}_{ij} + \beta_4 \text{ valenceC}_{ij} + \beta_5 \text{ arousalC}_{ij} \\ & + \beta_6 \text{ imp. of. moodC}_{ij} + \beta_7 \text{ attentionC}_{ij} + \beta_8 \text{ activity1C}_{ij} + \cdots \\ & + \beta_{18} \text{ activity11C}_{ij} + \beta_{19} \text{ presence. of. others1C}_{ij} \\ & + \beta_{20} \text{ presence. of. others2C}_{ij} + R_{ij} \end{aligned}$$

Level 2 equation:

$$\begin{aligned} \beta_{0j} = \ & \gamma_{00} + \gamma_{01} \text{ valenceM}_j + \gamma_{02} \text{ arousalM}_j + \gamma_{03} \text{ imp. of. moodM}_j + \gamma_{04} \text{ attentionM}_j \\ & + \gamma_{05} \text{ activity1M}_j + \cdots + \gamma_{015} \text{ activity11M}_j \\ & + \gamma_{016} \text{ presence. of. others1M}_j + \gamma_{017} \text{ presence. of. others2M}_j \\ & + \gamma_{018} \text{ sex}_j + \gamma_{019} \text{ age}_j + \gamma_{020} \text{ intensity. musicpreference}_j \\ & + \gamma_{021} \text{ musical. taste1}_j + \cdots + \gamma_{026} \text{ musical. taste6}_j + \gamma_{027} \text{ big5.1}_j + \cdots \\ & + \gamma_{031} \text{ big5.5}_j + \gamma_{032} \text{ gold. msi1}_j + \cdots + \gamma_{036} \text{ gold. msi5}_j + U_{0j} \end{aligned}$$

Step C

Level 1 equation:

$$\begin{aligned} Y_{ij} = \ & \beta_{0j} + \beta_1 \text{ intel. stimulatonC}_{ij} + \beta_2 \text{ mind. wanderingC}_{ij} \\ & + \beta_3 \text{ motor. synchronizationC}_{ij} + \beta_4 \text{ updating. musical. knowledgeC}_{ij} \\ & + \beta_5 \text{ killing. timeC}_{ij} + R_{ij} \end{aligned}$$

Level 2 equation:

$$\begin{aligned} \beta_{0j} = \ & \gamma_{00} + \gamma_{01} \text{ intel. stimulationM}_j + \gamma_{02} \text{ mind. wanderingM}_j \\ & + \gamma_{03} \text{ motor. synchronizationM}_j + \gamma_{04} \text{ updating. musical. knowledgeM}_j \\ & + \gamma_{05} \text{ killing. timeM}_j + U_{0j} \end{aligned}$$

For Step A and C Y_{ij} denotes the expected musical characteristic selected by person j at situation i. For Step B Y_{ij} denotes the expected function of music listening used by person j at situation i. In all steps β_{0j} represents a participant-specific intercept. This intercept is modeled following the level 2 equation including all person-related variables. Within-subject effects are represented by the beta coefficients (β_1–β_{25}) while γ_{01}–γ_{041} represent between-subject effects. Capital letter C denotes within-subject centered variables while M denotes aggregated variables at person level. The terms R_{ij} and U_j denote residuals at levels 1 and 2.

Modeling Results

Step A. Fixed Effects Estimates (Top) and Standard Deviation of Random Parameters (Bottom) for Models of the Predictors of Music Selection.

Parameter	calming–exciting	slow–fast	sad–happy	less melodic–very melodic	less rhythmic–very rhythmic	simple–complex	peaceful–aggressive	less intense–very intense
				Fixed Effects				
Intercept	1.38 (0.06)***	4.12 (0.06)***	4.44 (0.06)***	4.93 (0.06)***	4.58 (0.07)***	4.00 (0.06)***	3.26 (0.05)***	2.72 (0.06)***
Level 1 (situational)								
Mood								
Valence	0.06 (0.02)**	0.04 (0.02)	0.20 (0.02)***		0.06 (0.02)***			
Arousal	0.10 (0.02)***	0.04 (0.02)**			0.05 (0.02)**		0.05 (0.02)***	0.05 (0.02)***
Importance of mood	0.04 (0.01)*			0.09 (0.01)***				0.08 (0.01)***
Attention	0.12 (0.02)***	0.05 (0.02)**			0.06 (0.01)***	0.10 (0.01)***	0.02 (0.02)	0.23 (0.02)***
Activity[a]								
Pure music listening	-0.15 (0.06)**	-0.09 (0.06)**					-0.09 (0.06)	0.17 (0.06)**
Housework	0.07 (0.06)	0.05 (0.06)					-0.07 (0.07)	0.11 (0.06)
Working & studying	-0.38 (0.07)***	-0.36 (0.07)***					-0.42 (0.07)***	0.12 (0.07)
Coping with emotions	-0.50 (0.15)**	-0.99 (0.15)***					-0.38 (0.15)*	0.18 (0.15)
Exercise	0.67 (0.14)***	0.38 (0.14)**					0.81 (0.14)***	0.15 (0.14)
Social activity	0.01 (0.10)	0.04 (0.10)					-0.10 (0.10)	0.13 (0.10)
Party	-0.64 (0.26)*	-0.30 (0.26)					0.06 (0.26)	-0.42 (0.26)
Making Music	-0.29 (0.16)	-0.03 (0.16)					0.05 (0.16)	-0.02 (0.16)
Relaxing & falling asleep	-0.96 (0.10)***	-0.77 (0.10)***					-0.62 (0.11)***	-0.09 (0.10)
Personal hygiene	0.27 (0.11)*	0.14 (0.11)					0.01 (0.11)	-0.04 (0.11)
Other activities	-0.02 (0.12)	-0.17 (0.12)					-0.09 (0.12)	0.21 (0.12)
Presence of others[b]								
Others present & no interaction							-0.04 (0.06)	
Others present & interaction							-0.28 (0.07)***	
Level 2 (person-related)								
Mood								
Arousal	0.21 (0.07)**							
Attention	0.26 (0.07)***							0.44 (0.07)***
Musical taste								
Pop	0.10 (0.04)**							
				Random parameters				
Level 2								
Intercept/intercept (*SD*)	0.55***	0.54***	0.63***	0.64***	0.76***	0.58***	0.50***	0.56***

Note. Standard errors are in parentheses. SD = standard deviation. Based on a total of 2674 daily life assessment from N = 119 participants. The table only includes predictors that at least have been selected in one of the eight models. For a full list of included variables in the selection process of the percentile-Lasso see Step A equations. [a] Activity comprised 12 categories, reference category: being on the move. [b] Presence of others comprised 3 categories, reference category: alone. * $p < .05$. ** $p < .01$. *** $p < .001$.

Step B. Fixed Effects Estimates (Top) and Standard Deviation of Random Parameters (Bottom) for Models of the Predictors of Functions of Music Listening.

Parameter	Intellectual stimulation	Mind wandering & emotional involvement[a]	Motor synchronization & enhanced well-being	Updating ones musical knowledge[b]	Killing time & overcoming loneliness
			Fixed Effects		
Intercept	-0.67 (0.08)***	-2.22 (0.09)***	4.21 (0.09)***	2.30 (0.08)***	6.18 (0.08)***
Level 1 (situational)					
Indiv.Time			-0.02 (0.01)***		0.00 (0.02)
Indiv.Time²		0.001 (0.0003)**			-0.00 (0.00)
Weekend	-0.05 (0.04)	-0.07 (0.04)			-0.04 (0.04)
Mood					
Valence	0.03 (0.02)		0.12 (0.02)***		0.03 (0.02)
Arousal	0.05 (0.02)**	0.06 (0.02)***	0.03 (0.02)		0.03 (0.02)*
Importance of mood	0.13 (0.01)***	0.18 (0.01)***	0.12 (0.01)***		0.02 (0.01)
Attention	0.19 (0.02)***	0.22 (0.02)***	0.14 (0.02)***		
Activity[c]					
Pure music listening	0.30 (0.06)***	0.11 (0.06)	0.09 (0.06)		-0.28 (0.06)***
Housework	0.06 (0.06)	-0.12 (0.06)	0.51 (0.06)***		0.32 (0.07)***
Working & studying	0.41 (0.07)***	-0.10 (0.07)	-0.05 (0.07)		0.01 (0.06)
Coping with emotions	0.67 (0.15)***	0.63 (0.15)***	-0.84 (0.15)***		-0.46 (0.15)**
Exercise	-0.16 (0.14)	-0.25 (0.14)	1.10 (0.14)***		-0.03 (0.14)
Social activity	0.06 (0.10)	0.00 (0.10)	0.11 (0.10)		-0.04 (0.10)
Party	-0.29 (0.26)	-0.65 (0.26)*	0.74 (0.26)**		-0.32 (0.26)
Making Music	1.21 (0.16)***	0.12 (0.16)	0.03 (0.16)		-0.94 (0.16)***
Relaxing & falling asleep	0.25 (0.10)*	0.30 (0.11)**	-0.44 (0.10)***		-0.35 (0.11)***
Personal hygiene	-0.06 (0.11)	-0.28 (0.11)*	0.31 (0.11)**		0.34 (0.11)**
Other activities	0.21 (0.12)	-0.07 (0.12)	0.09 (0.12)		0.14 (0.12)
Presence of others[d]					
Others present & no interaction				-.20 (0.05)***	0.12 (0.06)*
Others present & interaction				.26 (0.06)***	-0.24 (0.07)***
Level 2 (person-related)					
Importance of mood	0.21 (0.08)**	0.27 (0.08)**			
Attention	0.40 (0.11)***	0.53 (0.12)***			
Age					-0.08 (0.02)***
Personality traits					
Openness to experience		0.56 (0.23)*			

(continued)

Step B. (continued)

Parameter	Intellectual stimulation	Mind wandering & emotional involvement[a]	Motor synchronization & enhanced well-being	Updating ones musical knowledge[b]	Killing time & overcoming loneliness
			Fixed Effects		
Gold MSI					
Active engagement	0.29 (0.10)**				
			Random parameters		
Level 2 (*SD*)					
Intercept/intercept	0.85***	0.93***	0.91***	0.84****	0.87***

Note. Standard errors in parentheses. SD = standard deviation.
Based on a total of 2674 daily life assessment from N = 119 participants. The table only includes predictors that at least have been selected in one of the eight models. For a full list of included variables in the selection process of the percentile-Lasso see Step B equations.
[a] For this model Indiv.time² was excluded from the random effects test as it caused estimation problems. [b] For this factor the 95th percentile of the percentile-lasso revealed to be too conservative and did not select any variables. We used the 93rd percentile instead, which was the nearest percentile for which a variable was selected. [c] activity comprised 12 categories, reference category: being on the move. [d] presence of others comprised 3 categories, reference category: alone.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Step C. Fixed Effects Estimates (Top) and Standard Deviation of Random Parameters (Bottom) for Models of the Predictors of Music Selection.

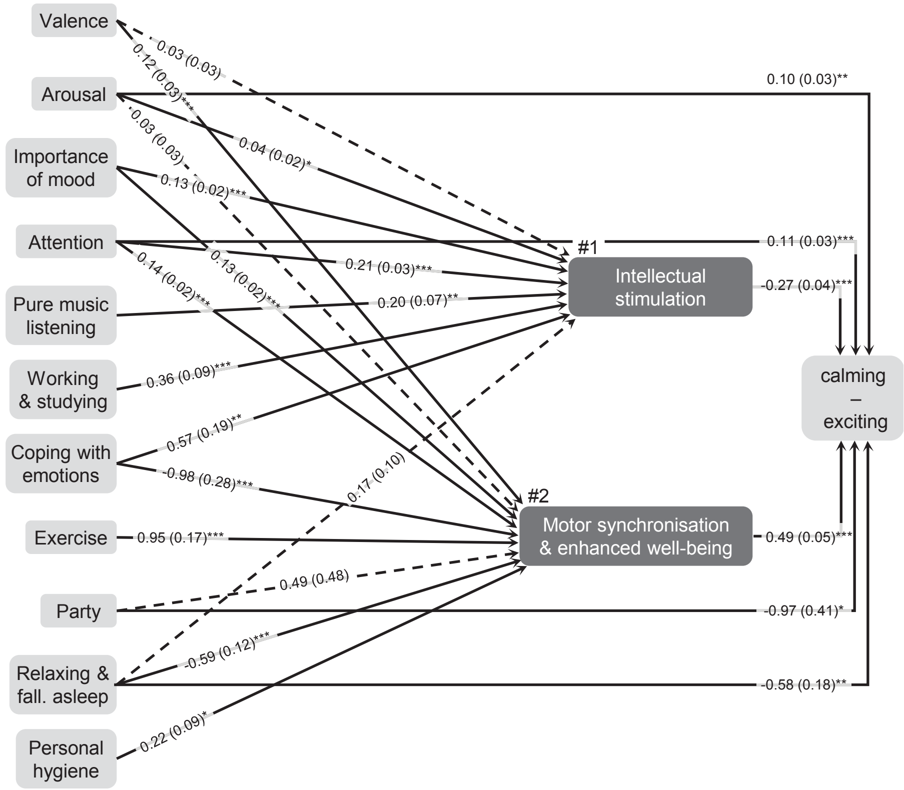
Parameter	calming–exciting	slow–fast	sad–happy	less melodic–very melodic	less rhythmic–very rhythmic	simple–complex	peaceful–aggressive	less intense–very intense
				Fixed Effects				
Intercept	4.15 (0.06)***	4.12 (0.05)***	3.63 (0.05)***	4.93 (0.06)***	4.57 (0.07)***	3.95 (0.05)***	3.26 (0.05)***	3.83 (0.06)***
Level 1 (situational)								
Intellectual stimulation	-0.22 (0.02)***	-0.21 (0.02)***	-0.19 (0.02)***	0.20 (0.02)***		0.38 (0.02)***	-0.12 (0.02)***	0.28 (0.02)***
Mind wandering & emotional involvement		-0.09 (0.02)***		0.12 (0.02)***		-0.02 (0.02)	-0.12 (0.02)***	0.15 (0.02)***
Motor synchronization & enhanced well-being	0.56 (0.02)***	0.50 (0.02)***	0.44 (0.02)***	-0.06 (0.02)**	0.33 (.02)***	-0.02 (0.02)	0.31 (0.02)***	0.10 (0.02)***
Updating ones musical knowledge				-0.09 (0.02)***		-0.03 (0.02)		-0.10 (0.02)***
Killing time & overcoming loneliness			-0.04 (0.02)			-0.03 (0.02)		-0.06 (0.02)**
Level 2 (person-related)								
Intellectual stimulation			-0.22 (0.07)***			0.23 (0.06)***		0.20 (0.07)**
Mind wandering & emotional involvement			-0.11 (0.06)					0.22 (0.06)***
Motor synchronization & enhanced well-being			0.48 (0.06)***					
Updating ones musical knowledge						-0.10 (0.07)		-0.24 (0.07)***
Killing time & overcoming loneliness						-0.13 (0.06)*		
				Random parameters				
Level 2								
Intercept/intercept (SD)	0.64***	0.54***	0.49***	0.64***	0.76***	0.53***	0.50***	0.54***

Note. Standard errors in parentheses. SD = standard deviation.
Based on a total of 2674 daily life assessment from N = 119 participants.
* p < .05. ** p < .01. *** p < .001.

Detailed Results of MSEM mediation analyses

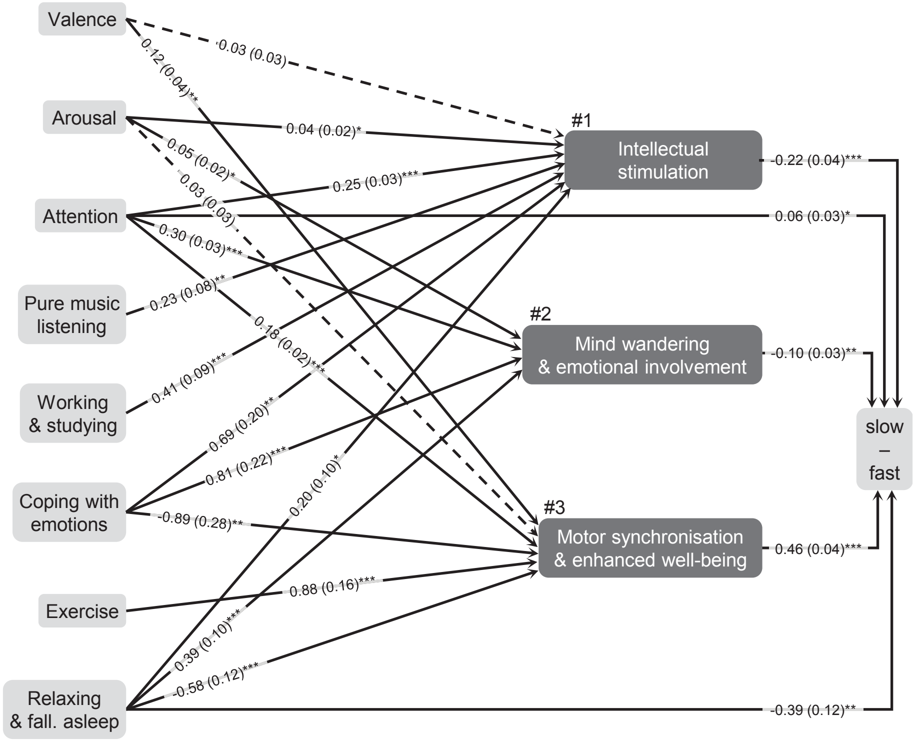
a)

#	Est.	(SE)	p
1:	-0.01	(0.01)	.29
2:	0.06	(0.02)	.001
1:	-0.01	(0.01)	.019
2:	0.02	(0.01)	.27
1:	-0.04	(0.01)	< .001
2:	0.06	(0.01)	< .001
1:	-0.06	(0.01)	< .001
2:	0.07	(0.01)	< .001
1:	-0.05	(0.02)	.013
2:	–		–
1:	-0.10	(0.03)	.002
2:	–		–
1:	-0.15	(0.06)	.013
2:	-0.48	(0.16)	.002
1:	–		–
2:	0.46	(0.10)	< .001
1:	–		–
2:	0.24	(0.23)	.30
1:	-0.05	(0.03)	.10
2:	-0.29	(0.06)	< .001
1:	–		–
2:	0.11	(0.05)	.020



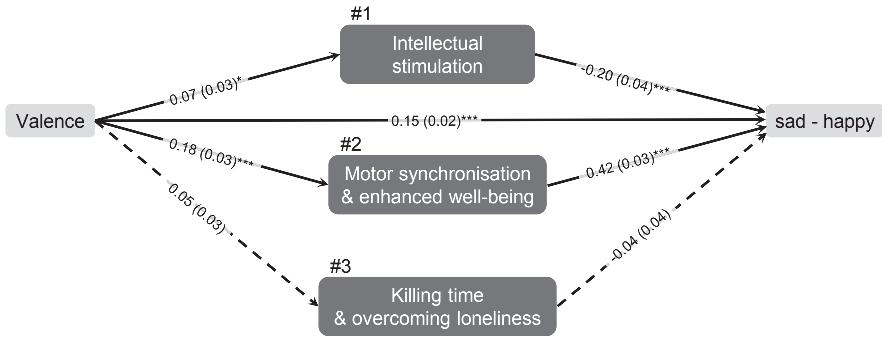
b)

#	Est.	(SE)	p
1:	-0.01	(0.01)	.34
2:	–		–
3:	0.05	(0.02)	< .001
1:	-0.01	(0.004)	.020
2:	-0.01	(0.003)	.078
3:	0.01	(0.01)	.27
1:	-0.06	(0.01)	< .001
2:	-0.03	(0.01)	.004
3:	0.08	(0.01)	< .001
1:	-0.05	(0.02)	.009
2:	–		–
3:	–		–
1:	-0.09	(0.03)	.002
2:	–		–
3:	–		–
1:	-0.15	(0.06)	0.12
2:	-0.08	(0.03)	.006
3:	-0.41	(0.15)	.005
1:	–		–
2:	–		–
3:	0.41	(0.08)	< .001
1:	-0.05	(0.02)	.060
2:	-0.04	(0.02)	.014
3:	.27	(0.06)	< .001



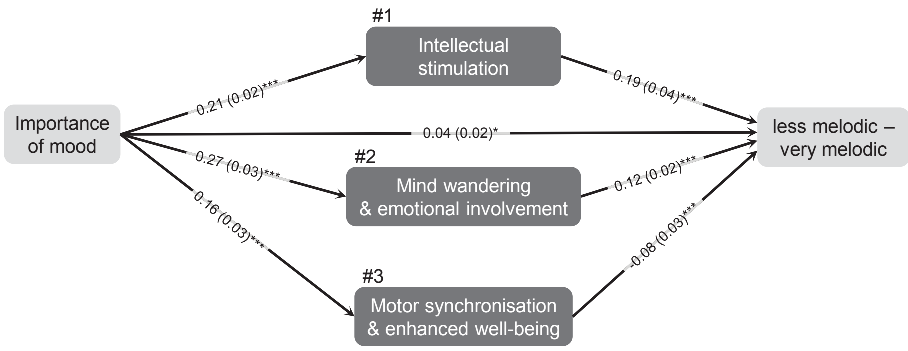
c)

#	Est.	(SE)	p
1:	-0.01	(0.01)	.028
2:	0.07	(0.02)	< .001
3:	-0.002	(0.002)	.26



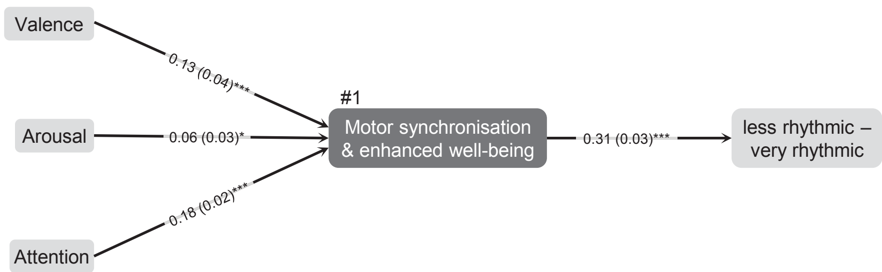
d)

#	Est.	(SE)	p
1:	0.04	(0.01)	< .001
2:	0.03	(0.01)	< .001
3:	-0.01	(0.01)	.006



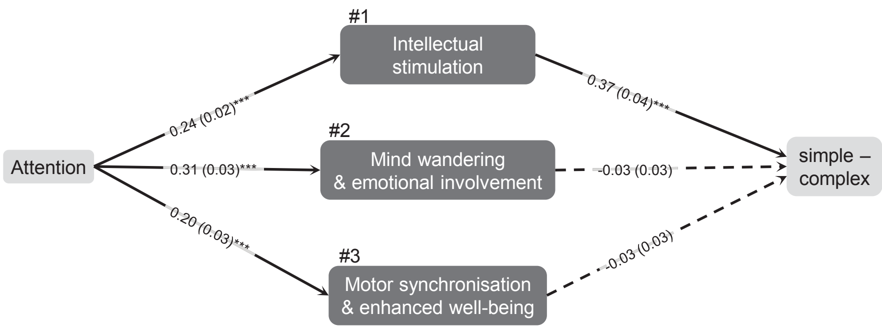
e)

#	Est.	(SE)	p
1:	0.04	(0.01)	< .001
1:	0.02	(0.01)	.044
1:	0.06	(0.01)	< .001



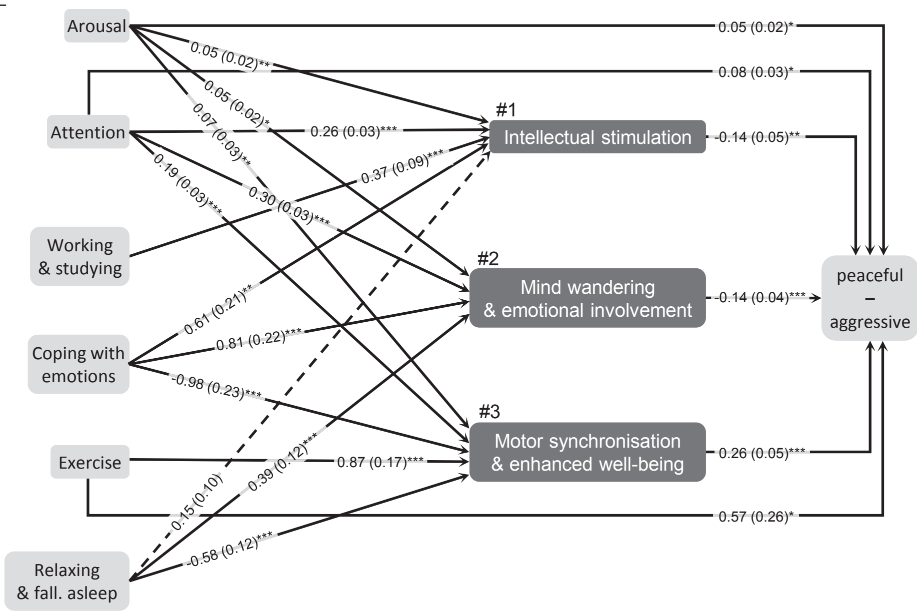
f)

#	Est.	(SE)	p
1:	0.09	(0.01)	< .001
2:	-0.01	(0.01)	.31
3:	-0.01	(0.01)	.30



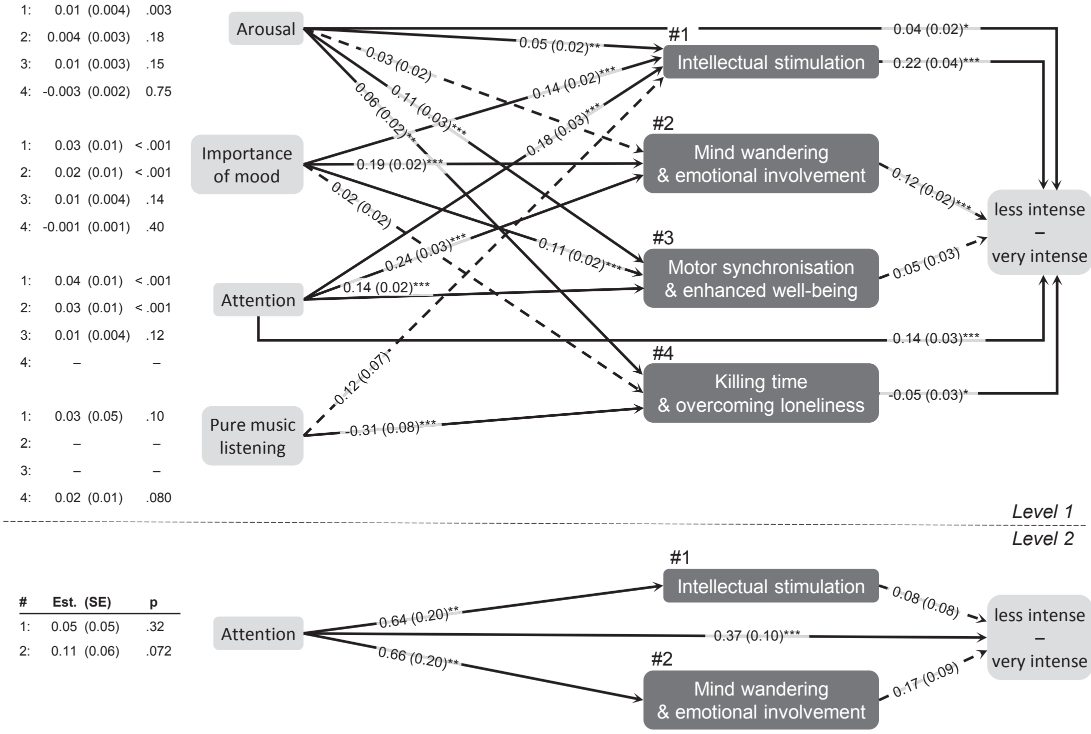
g)

#	Est. (SE)	p
1:	-0.01 (0.003)	.32
2:	-0.01 (0.004)	.097
3:	0.02 (0.01)	.013
1:	-0.04 (0.01)	.006
2:	-0.04 (0.01)	< .001
3:	0.05 (0.01)	< .001
1:	-0.05 (0.02)	.033
2:	–	–
3:	–	–
1:	-0.08 (0.05)	.071
2:	-0.11 (0.03)	< .001
3:	-0.26 (0.10)	0.10
1:	–	–
2:	–	–
3:	0.23 (0.07)	< .001
1:	-0.02 (0.02)	.18
2:	-0.05 (0.02)	.006
3:	-0.15 (0.04)	< .001



h)

#	Est. (SE)	p
1:	0.01 (0.004)	.003
2:	0.004 (0.003)	.18
3:	0.01 (0.003)	.15
4:	-0.003 (0.002)	0.75
1:	0.03 (0.01)	< .001
2:	0.02 (0.01)	< .001
3:	0.01 (0.004)	.14
4:	-0.001 (0.001)	.40
1:	0.04 (0.01)	< .001
2:	0.03 (0.01)	< .001
3:	0.01 (0.004)	.12
4:	–	–
1:	0.03 (0.05)	.10
2:	–	–
3:	–	–
4:	0.02 (0.01)	.080



#	Est. (SE)	p
1:	0.05 (0.05)	.32
2:	0.11 (0.06)	.072