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Artificial Intelligence-Driven Music Biometrics Influencing Customers' Retail Buying Behavior

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Manuscript Title

Artificial Intelligence-Driven Music Biometrics Influencing Customers' Retail Buying Behavior

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Response to Editors

Dear Editors,

We write to confirm that the final version of our paper is now formatted as per the guidelines of JBR. In addition, this version of the paper has also undergone professional language editing. Thank you.

Cordially,

The Authors

Artificial Intelligence-Driven Music Biometrics Influencing Customers' Retail Buying Behavior

Abstract

This study examines the digital transformation effects of artificial intelligence (AI)-based facial and music biometrics on customers' cognitive and emotional states, and how these effects influence their behavioral responses in terms of value creation. Using a real-life, major optical retail store in China, 386 customers participated in a five-day experiment with different types of music (enhanced by music-recognition biometrics). The findings show that for utilitarian-type customers in a high-involvement AI purchase condition, music-recognition biometric-induced emotion mediates cognition and behavioral intentions. Both likability and the tempo of the music affect the impact of music on cognition. This study contributes to a better understanding of the relationship between cognition and emotion induced by AI-based facial and music biometric systems in shaping customer behavior and it adds to the atmospheric literature. This is a significant contribution given the paucity of research in the context of the Chinese retail environment, which is now a significant retail market with global importance.

Keywords: Artificial Intelligence, Atmospherics, Cognition, Emotion, Music, Retail

1. Introduction

One of the most vital matters in the psychology of music is how music shapes emotional experience (Juslin, 2019). Music can be described as an "atmospheric influence" in traditional in-store retail settings. Moreover, music can shape shoppers' emotions—specifically arousal and pleasure—and their ensuing shopper behavior (Oakes et al., 2013; Roschk, Loureiro, & Breitsohl, 2017). The wide-ranging and commanding properties of music have validated it as having a strategic atmospheric influence on consumer behavior. These implications stimulate the need to distinguish music as an antecedent or driver of customer engagement that provides a wide-ranging, conceptual customer-engagement context from the perspective of shoppers (Leung, Paolacci, & Puntoni, 2018; Luo, Tong, Fang, & Qu, 2019).

Furthermore, recent literature (Prentice & Nguyen, 2020; Yang, Ji, & Tan, 2020) suggests that AI apparatuses are increasingly being deployed to influence customers' service experience. In addition, Berry, Wall, and Carbone (2006) indicated that experiences play different roles in customers' cognitive and emotional perceptions of the organization's service dimension. Such perceptions inspire customers' affiliation to and relationship with the organization, and, in turn, their retention within the organization (Degbey, 2015, 2016). Therefore, this research paper aims to highlight the use of AI-based information systems utilizing music as a biometric that can influence business decisions in organizations (Rodgers & Al Fayi, 2019; Rodgers, Al Fayi, Al-Refiay, & Murray, 2020; Rodgers, Mubako, & Hall, 2017). For instance, in an increasingly competitive retail market environment, retailers must continually discover new ways to satisfy their customers, and AI is promising in that regard. The term "artificial intelligence" describes computing systems that exhibit some form of human intelligence. It covers many interlinked technologies, including data mining, machine learning, speech recognition, image recognition, and sentiment analysis (Ferraris, Mazzoleni, Devalle & Couturier, 2019; National Science & Technology Council, 2016; Olson & Levy, 2018; Rodgers, 2020; Rodgers, Attah-Boakye, & Adams, 2020; Rialti, Zollo, Ferraris, & Alon, 2019).

Music's in-store influence has been broadly researched and linked with a range of anticipated marketing outcomes (North & Hargreaves, 1998; Oakes et al., 2013; Turley & Milliman, 2000). Music's effect on the mind and body has long been acknowledged in many settings (Oakes, Brownlie, & Dennis, 2014). For instance, some researchers have indicated that playing classical music amplified shoppers' consuming behavior in a restaurant, as it produced an added, refined atmosphere (North, Shilcock, & Hargreaves, 2003). Moreover, AI-based biometrics, such as for facial recognition and music, serve as the springboard for value-creation innovation, which captures customers' cognitive and emotional states and generates behavioral responses. In other words, the sound waves produced by music passing through customers' bodies can be used to identify their preferences (Sim et al., 2018), leading to enhanced profits via a reduction in negative costs, for example, those associated with long service waiting times.

Machine learning and deep learning are used to train computers to distinguish patterns in a similar manner to the human brain (Rodgers, 2020). These tools learn from examples and the experience gained from, for example, music, instead of employing hard-coded programming rules, and they utilize this learning to answer questions. Furthermore, pleasurable music may lead to the release of neurotransmitters associated with reward, such as dopamine (Gebauer & Kringelbach, 2012; Juslin, 2019). Department stores employing machine learning or deep learning apparatuses can enhance customers' moods or relieve their stress while they are shopping. In other words, listening to music can regulate, enhance, and diminish undesirable emotional states when customers are exposed to music while shopping (e.g., stress, fatigue).

This study proposes a conceptual framework by employing the throughput (TP) model to determine the digital transformation effects of music on customers' perceptions, judgments, and decision choices in terms of value creation. Researchers have applied and discussed the TP model in different decision-making contexts (Foss & Rodgers, 2011; Rodgers, 1997; Rodgers & Al Fayi, 2019; Rodgers, Alhendi, & Xie, 2019; Rodgers, Al Shammakhi, Johansson, Wincent, & Adams, 2020). This model employs "algorithms" that align with the discussion on AI-based systems (National Science & Technology Council, 2016), showing the impact of digital transformation on value creation.

This paper is motivated by the use of the AI-infused apparatus of facial and music recognition to enhance value creation when incorporated in a TP model. Facial recognition is a biometric technology that utilizes unique facial features to recognize individuals (Rodgers, 2010, 2012). This process begins with a webcam that captures customers' faces. This process continues by depicting the type of music signals that influence these customers in terms of them staying longer in the store, as they enjoy the department store's music-streaming system (see Figure 1). The next step involves how perception influences the customers' judgment, and this stage involves analyzing the type of music that the customers enjoy before a decision choice is made regarding value creation. Combining the AI tools of facial and music recognition with the TP model provides value creation for an organization.

Insert Figure 1

Figure 1 provides a depiction of how today's retailing landscape has shifted from a transaction-based approach to creating a pleasing and engaging shopping experience for customers in order to develop a lasting relationship; it is no longer a case of merely selling a product, but instead it is about the overall shopping experience from the time customers enter the shop until they leave. Morrison, Gan, Dubelaar, and Oppewala (2011) argue that the provision of a pleasant and exciting shopping ambiance and environment can go a long way toward providing an organization with critical differentiating factors (e.g., through specific environmental cues and stimuli, such as music, lighting, color, and aroma). Kotler (1973) suggests that in-store atmospherics and ambient conditions can increase customer purchasing probability. Atmospherics, a term coined by Kotler, is a message-creating medium and marketing tool that retailers use to develop environments that increase not only the time spent within their retail premises, but also customers' purchase likelihood—for example, in an expensively decorated, high-class restaurant that plays classical music. Prior studies have underscored the critical role of environmental conditions in retail stores and how these, in turn, can affect customers' purchase behaviors (Badrinarayanan & Becerra, 2019; Baker, Grewal, & Levy, 1992; Darden & Babin, 1994), store evaluations (Dubé & Morin, 2001), and satisfaction levels (Babin & Darden, 1996; Morrison et al., 2011). In general, positive in-store environments influence shopping activities positively, whereas negative environments create negative emotions and a general desire to leave the store (Babin & Attaway, 2000). Ever since the revolutionary idea that store atmospherics can affect customer behavior, retailers and manufacturers have sought ways in which to influence customers' "sensory experiences" (Spence, Puccinelli, Grewal, & Roggeveen, 2014).

The liking of a particular musical genre is primarily driven by human biometric–social identity. For example, someone who thinks of himself or herself as an intellectual may prefer jazz or classical music, while someone who views himself or herself in a more radical way may prefer rock or heavy metal. This paper defines AI-driven "biometrics" as a distinguishable physiological or behavioral feature that can help depict a user's identity (Rodgers, 2010). A social identity is the part of a person's self-concept derived from perceived membership in a relevant social group (Smaldino, 2019; Turner & Oakes, 1986). Therefore, age, gender, and socio-economic status, in addition to personality, may explain any biometric genre-based preferences. Biometrics may seem novel; nonetheless, it represents one of the oldest forms of identification (Rodgers, 2010). People recognize each other by sight from across the street, from voices on the telephone, signatures on contracts, and photographs on drivers' licenses. Fingerprints have been employed to identify people at crime scenes for more than 1000 years (Rodgers, 2010). What is innovative about biometrics used in marketing is that it may help identify different groups of music-oriented listeners (see, e.g. Martínez-López & Casillas, 2013). Therefore, our study centers on the music played and its possible influence on AI-driven biometric–social identity types.

The TP model with its algorithmic pathways relates to machine learning. That is, machine learning supported by the TP model can interject in the technological intersection of big data growth, decreasing data storage costs, enhancing computing power, and improving the acceleration of cloud computing. Machine learning algorithms represent the capability of computers to learn without specific programming (Cui, Wong, & Lui, 2006). Primarily, facial recognition biometric tools capture customers' facial expressions and then apply music-recognition biometrics to determine (by making a comparison to earlier facial expressions) if a particular type of music is more pleasurable for their shopping experience.

In other words, algorithms are at the heart of AI-based systems used in organizations. Specifically, this research underscores the rewards that Chinese retail stores can reap by combining product offerings with personalized services that require waiting time. Furthermore, this study scrutinizes the effect of music (in the TP model's information stage) on customers' cognitive (in the TP model's perception stage) and emotional (in the TP model's judgment stage) states, and how each state, in turn, influences the customers' behavioral responses in a real shopping environment (in the TP model's decision-choice stage).

2. Theoretical background

Fundamentally, music has three distinguishing parts: *time*, *pitch*, and *texture*. Volume subsidizes the *texture* of music and denotes the loudness or softness of the enacted musical passage (i.e., *pitch*) (Sinclair & Tinson, 2017). Tempo represents the speed or the pace (i.e., *time*), whereby a rhythmic pattern develops. Further, listening to music assists in shaping the mind that attends to it; hence, it diminishes the disorder we experience when random information inhibits us from achieving our objectives.

Thus, music is arguably one of the most potent and natural environmental stimuli to manipulate. It is also ubiquitous in contemporary society (Oakes et al., 2014). Prior research has shown that music in retail stores and other environments is a key atmospheric and environmental variable in eliciting a range of cognitive, affective, and behavioral customer responses (e.g., Alpert & Alpert, 1990; Areni, 2003; Baker et al., 1992; Garlin & Owen, 2006; Herrington & Capella, 1996; Knoferle, Spangenberg, Herrmann, & Landwehr, 2012; Milliman, 1982, 1986; Morin, Dubé, & Chebat, 2007; Morrison et al., 2011; North, Sheridan, & Areni, 2016; Oakes, 2003). Regarding the cognitive response, music can affect customers' perceptions of their waiting time; for example, they may perceive the time as shorter when music is present (Oakes, 2003) and liked (Yalch & Spangenberg, 1988). Regarding the emotional response, music can be a powerful stimulus, such that happy music can lead to a happy mood (Alpert & Alpert, 1990; Bruner, 1990), and sad music can evoke negative consumption emotions (Lin & Wu, 2006). Regarding the behavioral response, pleasant music can lead to stronger intentions to purchase (Morin et al., 2007; North et al., 2016), while slow-tempo music can prompt customers to stay longer in the venue and spend significantly more money (Milliman, 1982, 1986; see also Roschk et al., 2017 for a meta-analysis; Yalch & Spangenberg, 1993). Other studies have extended these works by focusing on music congruency—the joint effect of music and ambient stimuli, such as scent (Helmefalk & Hultén, 2017; Mattila & Wirtz, 2001) or lighting (Baker et al., 1992; Helmefalk & Hultén, 2017), product type (Areni & Kim, 1993; Imschloss & Kuehnl, 2019; North, Hargreaves, & McKendrick, 1999; Zellner, Geller, Lyons, Pyper, & Riaz, 2017), and product country of origin (North et al., 2016). Overall, mounting evidence reveals that music, when used effectively, can provide both direct (e.g., sales value and volume, repeat purchases) and indirect (e.g., positive perception of quality, store image) returns for firms.

Central to the study of the influence of environmental cues and stimuli on customer behavior is Mehrabian and Russell's (1974) S-O-R model, which posits that customer interactions with environmental stimuli (S) arouse a range of emotional states (O) that, in turn, trigger approach–avoidance behaviors (R). The S-O-R model is similar to the TP model's relationships depicted by customers' interactions with environmental stimuli (i.e., a perceptual interaction with information), their range of emotional states (i.e., perception), and triggering of approach–avoidance behavior, which is captured in the judgment and decision choice in the TP model. Moreover, approach behaviors include a desire to spend more time in store environments and enhance communications with others in that environment, while avoidance behaviors are the exact opposite. While many store atmospheric studies have adapted the S-O-R model (e.g., Chang, Eckman, & Yan, 2011; Choi & Kandampully, 2019; Donovan, Rossiter, Marcoolyn, & Nesdale, 1994; Sherman, Mathur, & Smith, 1997; Yalch & Spangenberg, 2000), most are limited by their sole focus on emotional states, while largely ignoring the role of cognitive factors (Baker, Parasuraman, Grewal, & Voss, 2002; Dubé & Morin, 2001; Sweeney & Wyber, 2002; Yalch & Spangenberg, 2000). Indeed, Yalch and Spangenberg (2000) attribute their findings of an indirect emotional effect on product evaluation to unmeasured cognitive factors.

The impact of music on cognitive responses has been discussed in studies on advertising (Kellaris & Rice, 1993; Lantos & Craton, 2012; MacInnis & Park, 1991; Oakes & North, 2013), store evaluation (Chebat, Chebat, & Vaillant, 2001), perceived wait duration (Antonides, Verhoef, & Van Aalst, 2002; Bailey & Areni, 2006; Oakes & North, 2008a), and in-store behaviors (Sweeney & Wyber, 2002). Chebat et al. (2001) show that music can stimulate the level of cognitive activity (i.e., the number of thoughts and the depth of information processing), which in turn affects store evaluation; however, their study omits the role of emotional factors. To overcome this gap, other studies have identified both emotional and cognitive states as mediators of music-induced behavioral outcomes in the context of a women's fashion store (Sweeney & Wyber, 2002) and undergraduate registration queues (Oakes & North, 2008a). In contrast, Cameron, Baker, Peterson, and Braunsberger (2003) found that mood alone mediates music and wait experience evaluations but not cognitive responses, such as wait-length valuation. Despite the important contributions of these studies, none discusses the potential mediating relationship of cognitive and affective responses on behavioral outcomes.

Customers' perceptions of waiting time in a service environment can affect their evaluations of the overall store experience (Grewal, Baker, Michael, & Voss, 2003); for example, a longer perceived or actual waiting time can be considered an added cost to customers (Kellaris & Kent, 1992), negatively affecting the store experience (Cameron et al., 2003; Hui, Dubé, & Chebat, 1997; Tom & Lucey, 1995). Therefore, customers' evaluations of a store or service environment will also take into account their perceptions of waiting time, particularly in store settings in which waiting is part of the purchase process (e.g., prescription glasses, pharmacies).

In their meta-analytic review of music's influence in retail settings, Garlin and Owen (2006) call for further research to examine both cognitive and affective responses as mediating variables. This is consistent with Bitner's (1992) servicescape framework, which encompasses both emotional and cognitive responses in determining the effect of environmental cues on customer behavior. As discussed previously, research that considers both cognitive and emotional factors relating to customer behavioral responses in a music-induced retail environment is still scant, as studies have mostly focused on emotional moderators, with only a few exceptions. However, the mediating relationship between cognitive and affective factors has not been considered (e.g., Cameron et al., 2003; Oakes & North, 2008a; Sweeney & Wyber, 2002); it may well be that cognitive responses mediate the music-induced emotional effect on customer behavior, or vice versa (Bitner, 1992). Schwarz (1990) suggests a bidirectional relationship between cognition and emotion, in which cognitive responses to a stimulus give rise to an emotion that, in turn, influences customers' responses to that emotion. Individual differences in the need for cognition or affection suggest that a greater understanding of this issue is warranted (Sweeney & Wyber, 2002). Moreover, Baker et al. (2002) found that music cues have different impacts on cognitive and affective responses. Thus, the relative contribution of these two types of responses in affecting behavioral intentions deserves additional research attention (Dubé & Morin, 2001; Morris, Woo, Geason, & Kim, 2002).

The current study aims to fill this gap by integrating wait perception with music-induced cognitive and affective responses and examining the mediating relationship between them. The study also considers the impact of music presence, tempo, liking, and customer gender and age. Previous studies have shown that simply playing any music is not sufficient, as different musical characteristics (e.g., tempo; Bruner, 1990; Kellaris & Kent, 1993; Kellaris & Rice, 1993) and personal musical taste (Gorn, 1982; Hui et al., 1997; Sweeney & Wyber, 2002) come into play to determine the predictive effect of music (Garlin & Owen, 2006). Research has called for studies to examine the role of personal factors such as gender and age (Bruner, 1990; Krishnan & Sexena, 1984; Otnes & McGrath, 2001), but music-related research, with the exception of a few studies (e.g., Grewal et al., 2003; Kellaris & Rice, 1993; Yalch & Spangenberg, 1990, 1993), has not given them adequate attention.

The current study employs the TP model (Rodgers 1991a, 1997, 1999, 2006; Foss & Rodgers, 2011) to organize several factors that affect individuals' use of information, which in turn influences their decision outcomes. The model is an extension of the rational perspectives on a decision. However, it allows for a more detailed analysis of the interaction effects between important factors during information processing, thus helping clarify the mediating relationship between cognitive and affective responses and its impact on behavior. Researchers have used the model extensively to examine managerial/corporate decision behavior (e.g., Foss & Rodgers, 2011; Rodgers, 1999; Rodgers & Gago, 2001), but, to the best of our knowledge, the current study is the first to use it in customers' decision processing. Thus, this study answers

Turley and Milliman's (2000) call for additional theory development to explain and predict atmospheric effects on customer behavior.

This research adds to the atmospheric literature through its exploration of the effects of music on customers' shopping experiences in a Chinese retail environment. The setting of the study is a major optical retail store in China. Cultural influences might have an impact on how customers perceive environmental cues (Turley & Milliman, 2000) and thus are an important addition given the paucity of research in this context, despite the emergence of China as a significant retail market in recent years due to government deregulation and the open-door policy from the late 1970s. Over time, the Chinese retail industry has become more market-oriented and customer-focused (Li, Zhou, Nicholls, Zhuang, & Kranendonk, 2004), as Chinese customers now seek satisfaction from positive shopping experiences, just as Western customers do (Davis, 2013; Wang, Li, & Liu, 2008). Although perceptions remain that Chinese customers' behavior and attitudes might differ from those of their Western counterparts, owing to the conflict between the Chinese traditional foundation and Western modernization, evidence now shows a convergence in consumption behavior and attitudes. Chinese customers are becoming more Westernized, and the same key factors relevant to Western customers, such as in-store stimuli (Zhou & Wong, 2004), patronage behavior (Davis, 2013; Tang, Chan, & Tai, 2001), store image, and shopping intention (Hu & Jasper, 2010), can affect their shopping experiences (Davis, 2013). Overall, the findings from these studies support the cross-cultural validity of the atmospheric model, and therefore the Chinese sample used in this study offers fertile ground on which to explore the antecedents of retail customer behavior further.

Much of the focus of previous work in this area has been on service retail environments for the purchase and consumption of services and non-durable goods (e.g., in supermarkets and restaurants; Milliman, 1982, 1986; Yalch & Spangenberg, 1988). Prescription glasses are durable goods that are not everyday purchases, and customers require help from the service staff throughout the shopping process. Optics are, therefore, a combination of both service and manufacturing elements (the glasses are produced in-store on the spot), which means that customers must often wait for up to an hour to collect their glasses. Grewal et al. (2003) call this an "intensive service" environment, which makes the issues surrounding cognitive and emotional responses to services and waiting time highly relevant. In addition, the use of an *in situ* research methodology allowed for the gathering of data in an actual retail setting to capture customers' moods and emotions more accurately during their exposure to the in-store environmental cues and stimuli.

In summary, this paper reports a field study to examine music's influence on customers' behavioral responses via the direct transfer of affection or by altering customers' cognitive responses (e.g., attitudes toward the store environment). In particular, the study uses the TP model to assess the mediating relationships between key variables affecting decisions. The study also attempts to explore the effect of music associated with different variances (i.e., likability and tempo).

3. Conceptual model and hypotheses

The conceptual model in Figure 2 represents the TP model process. From this, the impact of music on customers' cognitive and emotional responses and how these affect behavioral intentions can be presented in an organized manner. To clarify several critical algorithmic pathways, the TP model separates the decision-making process into four main concepts (see Figure 2): perception (**P**), information (**I**), judgment (**J**), and decision choice (**D**). In this model, perception and information are interdependent because information can influence how customers frame a problem (perception) or how they select the evidence (information) to be used in the decision-making process.

Insert Figure 2

The first processing stage involves the *framing* of a customer's environment. This means perceiving deviations (risk perceptions) from purchasing habits but also includes other internal and external informational factors that can affect the customers' response to store environments and their purchase intentions. Furthermore, perception (P) involves encoding information and framing the problem-solving set or view of the world (Foss & Rodgers, 2011). In this study, perception refers to customers' cognitive responses to the store environment as induced by the music played during their visit. For example, customers may categorize the store environment as enjoyable, rushed, or stressful. Information (I) here refers to the presence or absence of music in the store, and the music can have a fast or slow tempo and be liked or disliked. The double-ended arrow connecting perception and information in Figure 2 represents this relationship. Information can be portrayed via the different days of dissimilar music playing in the store. Information also includes the gender and age of the customers. In the judgment (J) stage, customers express emotional responses to the store environment. This stage also includes the development of alternative solutions or courses of action to purchase. Judgment contains the processes that people implement to analyze incoming information and the influences from the perception stage (Foss & Rodgers, 2011). Here, judgment refers to the impact of music on customers' emotional responses to the store environment. For example, customers may feel frustrated or irritated with the waiting time while in the store. Finally, decision choice (D) refers to customers' behavioral intentions, such as loyalty and overall satisfaction with the store. Table 1 lists the measures of the four constructs. Foss and Rodgers (2011) conceptualize the TP model as a way to organize the different stages, where interaction and ordering influence decision outcomes. This suggests that the direction of the mediating relationship between perception and judgment—that is, perception (cognitive responses) mediates judgment (emotional responses) or vice versa—can lead to different decision outcomes. The following five algorithmic pathways form the basis of the hypotheses:

P→D: Customers' perceptions of the store environment affect their behavioral intentions (decision choices).

P←→I: Customers' perceptions of the store environment mediate the information (characteristics of music and age), or vice versa.

P→J: Customers' perceptions of the store environment affect their emotional responses to the store environment (judgment).

I→J: Characteristics of music and customers' gender and age affect their emotional responses to the store environment (judgment).

J→D: Customers' emotional responses (judgment) to the store environment affect their behavioral intentions (decision choices).

Insert Table 1 here

3.1. Effect of music on cognitive responses (I→P→D)

Cognitive responses, such as perceptions, expectations, associations, and evaluations, derive from information-processing activities, such as perceiving, abstracting, and judging (Cacioppo, Harkins, & Petty, 1982). Music cues can affect cognitive processes in various ways. For example, in general, research finds that likable music helps reduce perceived waiting time (Garlin & Owen, 2006), though this finding is not always supported (e.g., Baker et al., 2002; Hui et al., 1997). Indeed, Kellaris and Kent (1992) find that pleasant music results in a longer perceived time duration, and they attribute this to a cognitive-psychological explanation of music's influence on perceived time. According to this theory, as listeners devote more attention to the music, they use more cognitive resources in the process, leading to the perception of a long lapse in time. Music can also influence customers' quality inferences about merchandise and services in the store, which can affect their perceptions of the store image.

For example, Baker, Grewal, and Parasuraman (1994) show that classical music produced expectations of prestige, while Top 40 music was associated with a discount image. However, this link is not consistently supported (see Yalch & Spangenberg, 1993). Chebat et al. (2001) demonstrate that cognitive processes, in terms of the number of thoughts and the depth of information processing, moderate customers' attitudes toward the store. For example, while slow-tempo music stimulated a more positive cognitive response and fast-tempo music stimulated cognition, the authors indicated a negative relationship between the level of cognitive activity and attitudes.

3.2. Effect of music on affective responses ($I \rightarrow J \rightarrow D$)

Prior research has empirically shown the association between music and customers' affective reactions, evaluations, and behavior (e.g., Hui et al., 1997; Oakes, 2003; Sweeney & Wyber, 2002). Some studies have demonstrated the effect of store atmosphere on customer behavior mediated by the customer's emotional state (e.g., Sherman et al., 1997). Research has also found that happy music can produce happier moods, while sad music may enhance purchase intentions (Alpert & Alpert, 1990). Alpert, Alpert, and Maltz (2005) provide a more explicit link between types of music and purchase intentions through the purchase occasion (i.e., sad music leads to a higher purchase intention for a "get-well card," while happy music is more effective in increasing the purchase intention for a "birthday-greeting card"). However, these findings pertained to music used in advertisements, so they may not necessarily apply to a store environment, as advertisements only last for a few minutes. Regarding the environmental impact on emotional states, Mehrabian and Russell's (1974) model proposes a mediation relationship between music (an environmental stimulus) and emotional states (e.g., pleasure, arousal), such that the interaction between pleasure and arousal affects individual behavior in that environment. A high level of pleasure leads to a longer stay in the store and more spending than was intended (Donovan et al., 1994; Roschk et al., 2017), whereas arousal tends to intensify pleasure or displeasure, as the case may be.

Research has shown that slow-tempo music greatly enhances affective responses compared with fast-tempo music, resulting in shorter time perceptions, improved satisfaction, and greater relaxation (Oakes, 2003), while likable music ameliorates negative emotional reactions to waiting time (Hui et al., 1997). Dubé and Morin (2001) find that customers have more positive store evaluations of—and attitudes toward—sales personnel when likable music is being played, and this positive affection grows stronger as the likability of the music intensifies.

3.3. Mediating role of emotional responses on the cognitive state (P→I→J→D), and vice versa (I→P→J→D)

The impact of music on cognitive, emotional, and behavioral responses has been the subject of many investigations, while the mediating role of emotional and cognitive responses has largely been neglected (Garlin & Owen, 2006). An exception is Demoulin's (2011) study, which examines emotional responses (pleasure and arousal) as a mediator between music congruency (i.e., between types of music and the physical atmosphere) and cognitive responses (service environment quality and service quality) in a French restaurant. Her results lend partial support to her proposition, as only pleasure mediates the music congruency–cognitive response relationship. Demoulin's (2011) study differs from the current research, as her independent variable was music congruency, which, according to prior work, enhances affective responses as a result of a more harmonious atmosphere being created (Oakes, 2007). This might have inadvertently led to heightened emotion compared with cognition.

Music appears to have a different impact on cognitive and affective responses, and the nature of this variation may fluctuate across different purchasing contexts (Baker et al., 2002) depending on customers' motivational orientation. Indeed, in a simulated online shopping environment, Kaltcheva and Weitz (2006) found that emotions such as arousal affect customers' behavioral intentions (e.g., to visit or to purchase) differently depending on their motivational orientation. They distinguish between two customer orientations—utilitarian (task-oriented) and hedonic (recreational)—and argue that because customers with a utilitarian orientation simply wish to complete their shopping as quickly and efficiently as possible, they find any environmental stimuli that cause high arousal unpleasant. Conversely, customers with a hedonic orientation seek satisfaction from the shopping activities themselves and thus find rich shopping experiences and high-arousal environments more pleasant. With this distinction, it could be argued that music is more likely to affect hedonic-oriented customers emotionally and utilitarian-oriented customers cognitively.

According to the central and peripheral processing theory (Petty, Cacioppo, & Schumann, 1983), when the product requires minimum motivation for cognitive processing, persuasive messages developed to achieve attitude change may be more effective when using simple cues such as background music (Kotler, 1973). Under such low-involvement conditions, both the cognitive and affective effects of music should have a significant impact (Bruner, 1990; Chebat et al., 2001) and be positive (Park & Young, 1986). Park and Young (1986) found that liked music had negative effects on customer attitudes under conditions of high cognitive involvement (perhaps due to distraction from the decision task) but positive effects under low cognitive-involvement conditions. Alpert and Alpert (1990) also argue that under low involvement, music is particularly effective in eliciting feelings and influencing behavior without necessarily affecting cognition. This perhaps explains why the mediational routes responsible for the effect of music on customers' responses tend to be predominantly affective, as most research has examined the impact of music under relatively low-involvement conditions, such as dining (Demoulin, 2011) and leisure shopping (Dubé & Morin, 2001;

Morrison et al., 2011; Yalch & Spangenberg, 2000). However, under high involvement, the impact of music on customers' responses is likely to be cognitive before it affects their feelings.

What is unclear from the existing literature, however, is whether emotion directly affects behavior or whether emotion influences perceptions by affecting moods and then prompting cognitive activity. Some studies have argued that customers may not be aware of the impact of their emotions on their cognitive state (Johnson & Tversky, 1983). It may be that both mediational routes are involved to one degree or another, leading to variations in the music-induced affective, emotional, and behavioral relationship.

The current study deems customer visits to the optical store for prescription glasses as a utilitarian shopping task. Prescription glasses sold in this experimental setting are relatively expensive and are purchased for daily or regular use. The monetary and functional value of the glasses suggests that customers consider them a high-involvement purchase. Thus, for utilitarian customers under a high-involvement condition:

H1 Music recognition (I) has a significant interactional effect on customers' cognitive responses (P) influenced by the likability and tempo of the music. That is, (a) likable music has an impact on customers' cognitive responses, and (b) slow music has a greater impact than faster music does on customers' cognitive responses.

H2 Customers' cognitive responses (P) induced by music have a significant, positive influence on their emotional responses (J).

H3 Customers' cognitive responses (P) induced by music have no effect on their behavioral intentions (D).

H4 The effect of music (I) has no direct effect on customers' emotional responses (J).

3.4. Impact of gender and age

In general, men and women respond differently to similar environmental stimuli (Mehrabian & Russell, 1974). Grewal et al. (2003) concluded that men perceive the store atmosphere less positively than women do and that they also have less tolerance for waiting than women do. Such differences between genders are consistent with the literature that suggests that men and women perceive time differently. For example, Krishnan and Sexena (1984) find that women tend to feel that time goes slower than men do. Kellaris and Rice (1993) also show that women respond more negatively than men do to loud music. Some studies have also shown that differences exist in women's and men's shopping behaviors (Dholakia, 1999; Kaltcheva & Weitz, 2006; Zeithaml, 1985). These studies suggest several reasons for this, including that women (often hedonic customers) tend to be more involved as shoppers who generally enjoy and spend more time shopping. Women are also less likely to simply want to get the shopping trip over with than men are (often utilitarian customers). Of more interest to the current study is the idea that male and female customers infer different meanings from music (Meyers-Levy & Zhu, 2010).

Age is an important factor in music preference (LeBlanc, Sims, Siivola, & Obert, 1996) and is likely to affect the impact of music as an atmospheric factor. Younger and older people tend to differ in their music preferences. The choices formed in the younger years tend to remain similar when one enters adulthood, but these preferences are likely to change as one gets older and, in the process, is exposed to more music, which may lead to new preferences (Russell, 1997). Holbrook and Schindler (1989) found that people tend to have higher preferences for songs that were popular when they were younger (i.e., aged 24 years) than for songs that gained popularity before and after that time in their lives. Yalch and Spangenberg (1988) indicate that shoppers under the age of 25 reported longer perceived shopping durations under an easy listening condition, while older shoppers believed they had shopped for longer when Top 40 music was played. The interactional interplay between gender and age with perception mimics a neural network apparatus by expressing the P←→I relationship, which implies that information updates perception (in a Bayesian sense), as well as perception influencing the types of information (i.e., heuristics, specialized processing, etc.) to be later processed by the judgment stage (Rodgers, 2010, 2012) (see Figure 2). Therefore:

H5 Gender (I) has a significant interactional effect on customers' cognitive responses (P).

H6 Age (I) has a significant interactional effect on customers' cognitive responses (P).

4. Research method

An experiment was conducted to investigate the hypotheses in a major optical retail store located in a midsize city in China using real customers. Experiments have proved to be an effective mechanism for understanding store environment experiences (e.g., Dubé & Morin, 2001; Eroglu, Machleit, & Chebat, 2005; Milliman, 1982; Morrison et al., 2011). The experiment was set up using unobtrusive measures (see Webb, Campbell, Schwartz, & Sechrest, 1966). That is, an unobtrusive measurement design was incorporated into our research since it allows for observations to be made without the knowledge of those being observed (Webb et al., 1966). Unobtrusive measures are designed to minimize a major problem in research design, which relates to how a subject's awareness of the research project may affect his or her behavior and distort the research results.

For this study, the unobtrusive measures for the AI biometric mechanisms were kept hidden, enabling the researcher not to be intrusive within the research context by not exposing this new technology. That is, AI biometric technology, when known, has caused responses that were not directly linked to the research (Rodgers, 2020). In other words, unobtrusive measurements presumably reduce the biases that result from the AI measurement instrument being intrusive. Therefore, by not mentioning the presence of the AI biometric apparatus, the indirect measurements were unobtrusive and occurred naturally in the research context. This design assisted in the collection of the data without introducing any formal measurement procedures that may have brought other antecedents into the research design.

Moreover, in constructing the questionnaire, unobtrusive measures are well suited to music studies that focus on processes that occur within a certain time period. While longitudinal surveys and long-term field observations are also suitable ways of gathering such information, they cannot examine processes that occur due to the introduction of novel AI methods, such as biometrics, nor are they the most cost-effective ways to examine long-range processes. Unobtrusive methods, on the other hand, enable researchers to investigate events and processes that have long since passed. They also do not rely on retrospective accounts, which may be subject to errors in memory, as some longitudinal surveys do. In sum, the strengths of unobtrusive research include the following:

1. There is no possibility of the Hawthorne effect.
2. The method is cost-effective.
3. It is easier in unobtrusive research than with other methods to correct mistakes.
4. Unobtrusive methods are conducive to examining processes that occur over time or in the past.

The participating store has been in the optical business for more than 30 years. A typical customer business transaction includes a personal consultation (e.g., eye examination) and product selection, followed by a waiting time (one hour on average) for the selected product to be fitted according to individual requirements. The experimental manipulation included four musical stimuli that varied according to two levels of music valence—likability (like and dislike) and tempo (slow and fast)—and a no-music control group. The likability factor was predetermined in a survey of 100 store customers randomly selected in the weeks before the actual experiment. The results revealed a list of Chinese singers and songs that the respondents liked to listen to and a corresponding list of those they did not like. A selection of songs from these two lists represented the liked and disliked music in the subsequent experiment. Milliman (1982) suggests the use of instrumental music for greater control of music variables (e.g., the gender of the singers); therefore, this type of music was used to vary the music tempo. Two music-tempo conditions were selected from the criteria used by Milliman (1986) and Gorn (1982): music with 94 or more beats per minute for the fast-tempo condition and music with 72 or fewer beats per minute for the slow-tempo condition. The experiment took place over five weekdays with liked and disliked music played on Days 1 and 2, respectively, slow- and fast-tempo music played on Days 3 and 4, respectively, and no music played on Day 5 (see Table 2). Saturday, Sunday, and public holidays were excluded to control for types and numbers of customers. The day of the week might also have an impact on the attitude toward waiting time, as this might have different cost implications for individual customers (Davis & Vollmann, 1990)—for example, waiting time may lead to a delay in getting to work. Perceptions of waiting costs (e.g., in terms of financial, opportunity, or social-emotional costs) affect overall experience evaluation (Cameron et al., 2003), and therefore the experiment only took place on weekdays.

Insert Table 2 here

Special measures were undertaken to ensure the consistency of the field setting across the five experimental days by controlling for environmental stimuli other than music that are potential influencers of customer behavior (e.g., music volume, store lighting, layout, and temperature). All music types were played at the same moderate volume level throughout the experiment. The experiment took place during the summer, and the outside temperature was consistently high during this period. To ensure that the heat did not affect customers' moods, the temperature in the store was a comfortable and consistent level throughout the five days. During the experimental period, each experimental treatment was run through its entire designated day (from store opening to closing), and the customers filled out a store exit survey after collecting their purchase. Shop assistants were on hand throughout the day to help customers complete the survey and to ensure they clearly understood the questions and responded accordingly. In order to control for potential variation in customer service quality, the same shop assistants were assigned to work across the five days. In total, 386 customers participated in the exit survey during the experiment (see Table 2).

The exit survey measured customers' emotional and behavioral responses induced by the presence (or absence) of music while in the store, including an evaluation of the store environment (e.g., rushed, stressful, tense), their emotional response to the wait (e.g., frustrated, irritated, dissatisfied), their approach behavior toward the store (e.g., "I will recommend the store to my relatives and friends"), and their overall satisfaction (e.g., "My decision to come to this store is wise"). These measures were adapted from Hui et al. (1997) and Westbrook and Oliver (1981), and they formed the constructs in the TP model (see Table 1). All scales were on a 7-point Likert format (7 = *strongly agree*, 1 = *strongly disagree*), where higher numbers indicate more positive emotional and behavioral responses. Negatively coded statements were reverse coded. The survey also included measures for a manipulation check (e.g., music likability, familiarity, tempo) and demographics (gender and age).

4.1. Sample and manipulation check

Most of the 386 respondents (56.4%) were between the ages of 20 and 40, and 60.2% of the sample was female. The manipulation of the experimental treatments was successful, as respondents preferred the music played on Day 1 (liked music) ($M = 3.85$, $SD = .813$) significantly more than the music played on Day 2 (disliked music) ($M = 2.18$, $SD = .908$; $t(156) = 12.19$, $p < .001$). Respondents' evaluations of the familiar and unfamiliar music served to test for confounding effects between familiarity with and the liking of the music. A paired sample *t*-test revealed a significant difference in familiarity with ($M = 3.07$, $SD = 1.087$) and liking of the music ($M = 3.25$, $SD = 1.042$; $t(314) = 2.769$, $p < .010$). This indicates the successful manipulation of music likability. Furthermore, possible confounding effects between liked music and the music tempo were examined by means of an analysis of variance (ANOVA), which revealed no significant difference between respondents who preferred either fast- or slow-tempo music or neither ($F(2,313) = .019$, $p > .10$). This suggests that liking did not differ between fast- and slow-tempo music.

As customers' responses in terms of both the independent and dependent variables came from self-reports, the survey contained several questionnaire-related design measures to control for potential common method bias (CMB) in the study. In line with Podsakoff, MacKenzie, Lee, and Podsakoff's (2003) suggestions, the survey guaranteed respondent anonymity and counterbalanced the order of questions. Two techniques were used to estimate potential CMB. First, Harman's single-factor test was implemented using exploratory factor analysis, in which all variables were loaded onto a single factor and constrained to avoid rotation. The test yielded ten factors, the largest of which accounted for 51% of the variance, just 1% over the recommended threshold of 50% (Podsakoff et al., 2003), suggesting the remote presence of CMB. Second, the common latent factor (CLF) method was used to introduce a new latent variable, such that all manifest variables were related to it. Those algorithmic pathways were constrained to be equal, and the variance of the common factor was constrained to be 1. A comparison of the standardized regression weights from the model with a CLF with the standardized regression weights of a model without the CLF indicates that CMB is not a significant threat after the removal of a question on "word of mouth."

4.2. Data analysis

Maximum likelihood helped assess the conceptual and measurement techniques executed by the software package LISREL (Jöreskog & Sörbom, 1993). A key forte of LISREL is its unobservable-element methodology to causal modeling testing, where several elements of each construct are attained. Several indicators enhance the construct validity of measurements and diminish measurement errors (Rodgers, 1997). LISREL also allows the following features for model testing: full information (e.g., maximum likelihood) estimation, statistical assessments of model fit and suggestions for improving the model, and the lessening of conventional regression expectations (i.e., no error term associations, no measurement error). This analysis interpreted the comparative fit index (CFI; Bentler, 1990), which estimates a population measure of the model fit. Bentler (1990) acknowledges that the CFI has less sampling variability than the normed fit index (NFI) or incremental fit index (IFI) do. Unlike the IFI, the CFI never exceeds 1 and avoids the NFI's small sample underestimation of the model fit. These three fit indices are, however, asymptotically comparable (Bentler, 1990). Last, causal estimates tested the models' free parameters, which confirmed how well the customers' model satisfied the parameter limits (James, Mulaik, & Brett, 1982).

There are several reasons for taking into consideration the use of structural equation modeling techniques (Rodgers, 1991b; Rodgers & Guiral, 2011). First, since many marketing concepts are abstractions, it is appropriate to distinguish between a hypothetical construct as an unobservable variable and an actual realization of it in a specific measured variable. Second, the actual realization of a construct is non-unique in that the same theoretical construct may be operationalized in a variety of ways. Therefore, we can envision a sphere of measured variables, all of which have the same underlying construct in common. Third, measured variables may comprise fallible measurements. Likewise, the variables may also include errors of measurement of an unsystematic nature. When variables consist of significant measurement errors, attempts to estimate structural parameters with measured variable methods may spearhead severe bias in the estimates. Fourth, the measured variables may consist of systematic or non-random sources of errors, such as variation due to method or content. These may produce severe bias in the estimates of the structural parameters. Finally, there may not be a way to formulate direct, single measures of the theoretical construct in question given that the effects of the theoretical construct may never be separated from the effects of other causal variables. Overall, it is such conditions that dictate the use of structural equation models that include both measured and unobservable variables. In sum, structural equation modeling techniques enable the researcher, by means of the choice of method and meticulous model specification, to determine the bearing of previous knowledge on the data to be analyzed (Rodgers, 1991b).

5. Results

A one-way ANOVA examined the effect of the type of music being played in the store on customers' perceptions. Welch's F test revealed a statistically significant main effect, indicating that different types of music had different effects on customers' perceptions (Welch's $F(4, 184.59) = 60.06$, $p < .001$; see Table 3), in support of H1a.

Insert Table 3 here

Post hoc Tukey's honest significant difference tests indicated that perception had a significantly ($p < 0.005$) lower average score ($M = 4.87$, $SD = 1.166$) when fast-tempo music was played than when slow-tempo music was played (see Table 3), in support of H1b. These results suggest that the type of music has an impact on customers' cognitive responses (perceptions).

Before the structural equation model analysis was conducted, a principal component analysis using SPSS was run on the 11 items with orthogonal rotation (Varimax)[1]. The Kaiser–Meyer–Olkin measure was .874 and the Bartlett's test of sphericity was $X^2(66) = 4064.1$ ($p < .001$). An initial analysis was run to obtain eigenvalues for each component in the data.

[1]. Both principal axis factoring and non-orthogonal rotation (oblique) were also run, and the results were largely similar.

Three components had eigenvalues over Kaiser's criterion of 1 and, in combination, explained 77.7% of the variance. Table 4 shows the factor loadings after rotation. The grouping of items on the same components suggests that the three components represent perception, judgment, and decision. The scales for the model construct had good internal consistency, as indicated by Cronbach's alpha.

Insert Table 4 here

Regarding the structural equation model, the chi-square test disclosed moderate discrepancies between the observed correlation matrix and that implied by the auditors' model (X^2 = 294, degrees of freedom = 60). Yet the goodness-of-fit index, NFI, IFI, and CFI values surpassed the 0.90 threshold for an acceptable fit (Bentler & Bonnet, 1980). Furthermore, the root mean square residual (0.04) indicated a good fit. Individual parameter estimates reported in Table 5 further corroborate this interpretation.

In Table 5, factor loadings are part of the measurement system parameters. The standardized regression weights for the factor loadings represent calculating observed variables from unobservable concepts. The variance of the latent variables is ascertained by the first indicator loading, which was set as equivalent to 1 on its latent variable. Note that, by and large, the factor loadings are high and uniform for each of the unobservable concepts under examination. In summary, the model assessed, with sound estimation precision, that the hypothetical concepts were present as unobservable concepts and that the observed concepts were reasonable pointers regarding these features. Table 6 shows the correlation matrix, means, and standard deviations of the model.

Insert Tables 5 and 6 here

In Table 4, the particulars related to the structural modeling factors can be understood through the following notation framework: each causal parameter evaluation comprises a subscript entailing two letters. These descriptions stem from the first letters of the corresponding concepts' terms conveyed by the concepts (customers' perceptions of the store environment on their judgment and decision choice: γ_{JPJ}, γ_{PD}; information effects on judgment through age: γ_{AJ} and music days: γ_{MJ}; and judgment on decision choice: γ_{JD}). The subscripts connected with the regression weights (directional arrows in the figures) are nested, such that the first subscript denotes the precursor concept (or "cause"), and the second depicts the dependent concept.

The results of a statistically significant interactional effect of music (I) on customers' cognitive responses (P) provide support for H1 ($p < 0.01$; see Table 4). H2 was also significant ($p < 0.01$), suggesting an effect from customers' cognitive responses (P) on their emotional responses (J). Cognitive responses (P) did not have a significant effect on behavioral intentions (D), in support of H3. In addition, the effect of music (I) did not directly affect customers' emotional responses (J), in support of H4. Age (I) had a significant interactional effect on customers' cognitive responses (P), in support of H6 ($p < 0.01$), while such an effect did not emerge for gender; thus, H5 was not supported.

The analysis results suggest that because the interactional effect between customers' cognitive responses (P) and age (I) was significant, as were the relationships of P→J and J→D, the I→P→J→D path was supported. However, no support was found for the I→J→D and P→J→D algorithmic pathways.

6. Discussion

6.1. Theoretical implications

This paper aimed to examine the extent to which value creation via store atmospherics can offer practical value to Chinese retail stores in general, but particularly to those that combine product offerings with personalized services that require waiting time. The study analyzed the effect of AI-induced biometric–social identity music on customers' cognitive and emotional states and how these, in turn, influenced their behavioral responses in a real shopping environment. The study was conducted in a real retail setting with naturally occurring customer behavior, which not only strengthens the external validity of the findings but also provides an opportunity to validate previous findings from experimental studies using only student samples (e.g., Chebat et al., 2001; Cameron et al., 2003; Grewal et al., 2003, Oakes & North, 2008b), which is common in atmospherics-related research.

Overall, the study confirms that a digital transformation brought about by AI-induced biometric–social identity music is an important environmental stimulus for customer behavior. Specifically, the results show that for utilitarian customers in a high-involvement purchase condition (i.e., high-value prescription glasses), music-induced emotion mediated their cognition and behavioral intentions. In effect, music altered the customers' thought processes, while cognition did not influence their behavior directly unless it also affected their emotions ($I \rightarrow P \rightarrow J \rightarrow D$ algorithmic pathway). This finding is consistent with the predictions of central and peripheral processing theory (Petty et al., 1983), which posits that music can have a lesser effect when customers are highly involved with the product; in such circumstances, music must be able to stimulate both cognitive and affective processes to influence behavior. However, the results contradict the findings of Cameron et al.'s (2003) study, which identifies mood as the mediator between music and overall experience evaluations. This inconsistency may be due to the low-involvement, low-cost wait situation in Cameron et al.'s (2003) study versus the high-involvement condition in the current study.

In contrast with prior studies (e.g., Hui et al., 1997; Oakes, 2003; Sweeney & Wyber, 2002), biometric–social identity music did not influence emotion directly. This is because utilitarian shoppers tend to come into the store with a clear purpose in mind and are therefore less likely to be stimulated by the presence of music. In contrast, hedonic shoppers are more likely to be swayed by music. According to Bruner (1990), when the environmental evaluation is based on cognitive appraisal, the presence of music can serve to distract from rather than pacify or enhance mood. Indeed, Kaltcheva and Weitz (2006) found that customers' motivational orientation moderates the effect of the pleasure or arousal produced by a store environment on shopping behavior.

In contrast, the likability and the tempo of the music affected the impact of AI-induced biometric–social identity music on cognition. A positive influence can occur if the right type of music is played; otherwise, music can be counterproductive. This is consistent with prior research that shows that shoppers listening to pleasant music while in a store (e.g., liked music, slow tempo) had a more positive experience than shoppers listening to unpleasant music did (e.g., disliked music, fast tempo), despite the waiting time (e.g., Cameron et al., 2003; Dubé & Morin, 2001; Hui et al., 1997; Oakes & North, 2008b).

Consistent with the literature, age significantly moderated the influence of music (Holbrook & Schindler, 1989; Yalch & Spangenberg, 1988, 1993). Age appeared to influence cognitive responses induced by music, but not emotional responses. This finding confirms the need to be aware of any trends in customers' age on different days and times of the week; for example, there might be more young shoppers during weekends than on weekdays. Retailers must consider this segmentation factor when deciding what music to play in the store.

However, contrary to some studies (e.g., Grewal et al., 2003; Kellaris & Rice, 1993), gender was not an important moderator.

This study adds to the extant literature on the relationship between cognition and emotion (e.g., Lazarus & Smith, 1988; Morris et al., 2002; Murry & Dacin, 1996) by empirically demonstrating, via the TP model (Rodgers et al., 2019), that in a high-involvement, utilitarian purchase condition, biometric–social identity music-induced emotion mediates the effect of cognition on customer behavior in a retail store environment. The findings lend support to the idea that different music attributes (e.g., likeability, tempo) lead to varying degrees of cognitive responses, which in turn shape the role of cognition in customers' responses to the emotion. Understanding the role of cognition and emotion in affecting customer behavior is particularly important when studying the impact of music in a store environment, as it is clear that retailers need to identify the type of music that will stimulate cognitive responses and, ideally, alter time perceptions to reduce the negative feeling generally associated with service waiting time (Cameron et al., 2003; Hui et al., 1997; Oakes & North, 2008a).

In addition, this study disclosed insights that may help better understand the fast-growing Chinese retail market (Wong & Dean, 2009), particularly in the context of using music as an environmental stimulus to improve shopping experiences. This is a relatively under-researched topic, and thus a systematic understanding of the Chinese shopping experience and the physical environment lags behind that of Western settings (Davis, 2013; Tang et al., 2001).

6.2. Managerial implications

The findings reveal that music is a tool to effectively manage innovative store atmospherics (e.g., Yalch & Spangenberg, 2000). Overall, the results are in line with the expectations of extant store atmospherics literature, which is primarily based on retail market settings in the West. Consequently, this study confirms that music is an influential environmental stimulus in affecting customer behavior across cultures. The universal appeal of music explains why, despite the complexity of effectively manipulating music to exert an influence on customer behavior or perception, it remains one of the most popular tools among retail stores, as it is relatively easy and economical to implement. The key challenge for retailers is making the best use of this tool based on an empirical understanding of its influence on customers' choice and overall shopping experience. For example, Chebat et al. (2001) allude to the evocative power of music in effecting deep cognitive responses in customers, but the extent to which a piece of music is evocative will depend on customers' gender, age, culture, and so on. Therefore, the ability to identify the right type of music is predicated on profound customer insights.

The role of customers' motivational orientation (i.e., utilitarian vs. hedonic) and product involvement (high vs. low) regarding the impact of music highlights the importance of the congruency between the types of music and the purchasing context (Chebat et al., 2001). It might be possible for retailers to use music to manipulate customers' motivational orientation, for example, from utilitarian to hedonic. Hedonic shoppers are more likely to spend more time in the store browsing and engaging in impulse buying (Beatty & Ferrell, 1998; Hausman, 2000). Moreover, the prevalence of internet shopping means that enhancing customers' shopping experiences in physical stores is more important than ever. Online shoppers tend to be more price-sensitive than offline shoppers due to easy access to price comparisons among rivals. Indeed, many online purchases stem from price promotions (Earl & Potts, 2000).

The capability of retailers to successfully utilize data analytics and other emerging technologies to meet changing customer expectations will be a fundamental factor of success in the future. These AI tools will also markedly affect operational activities, such as human resource management, supply chains, customer satisfaction, and sustainability efforts. Data and

AI algorithms can make an organization's merchandizing decisions more precise while restructuring operations and improving the customer experience.

Nonetheless, adding music technology, by itself, is not enough. Retailers must also rethink their in-service models throughout their stores, distribution centers, and headquarters. AI tools provide for organizations with fewer layers; therefore, each employee can be responsible for a more diverse set of responsibilities. Moreover, AI will embolden faster decision-making.

Therefore, to completely unravel the benefits of AI and music, organizations are encouraged to employ technological transformations and the widespread adoption of automation. Structurally, this implies moving from stringent hierarchies and siloed facilities to flexible resources that can enhance workflow. Furthermore, employees can be endowed with real-time data, and decision choices can be resolutely decentralized to cultivate an inclination toward action.

AI and automation technologies have immeasurably transformed every stage of the retail voyage, from inventory management to customer service. Retailers are also incorporating data analytics into many features of their businesses, encompassing sales predictions, store optimization, and product recommendations. As AI tools continue to emerge, coupled with managers' familiarization with the evolving technologies, AI will be indelibly inked into the minds of the consumers' buying experiences and expectations.

6.3. Limitations and future research

This research has several limitations that might offer opportunities for further AI-induced studies. First, the study used self-report measures, which may be subject to CMB (Podsakoff et al., 2003). However, both Harman's single-factor test and CLF estimates indicated no significant threat. In addition, previous studies have found consistency in self-report and more objective measures (Armitage & Conner, 2001). Second, the difficulty of interpreting the experimental effects of music on customer behavior (due to the confounding effect of different music properties from different pieces of music) to obtain a musical variable (e.g., liked or disliked music) makes isolating specific causal antecedents almost impossible (Kellaris & Kent, 1993; Yalch & Spangenberg, 2000). This is a commonly cited limitation in similar research. Although manipulation check measures were in place to ensure the validity of different experimental treatment conditions, not all differences might have been fully controlled for, suggesting caution in interpreting the results. Third, despite the substantial effort to control for potential effects of environmental elements (such as lighting, temperature, and so forth) on store atmosphere during the experiments, it is impossible to completely rule out whether customer responses were affected by environmental stimuli other than music in the retail setting. However, this potential shortcoming is outweighed by the benefits gained from the data being obtained in an actual rather than a hypothetical store. Fourth, customers' prior mood before entering the store was not measured to establish a baseline for comparing the impact of music on their emotions (Gardner, 1985; Sherman & Smith, 1987). However, such a measurement is difficult to achieve in a real-life retail setting because not all customers who walk into the store end up making a purchase. Last, the experiments were conducted within one retail store; thus, the ability to generalize is limited. Replication of this study in the context of other country settings would help determine whether the findings are universally applicable or culture-specific to China. However, regional differences in the market are quite common in China, and therefore the applicability of these results to other regions or cities remains to be tested.

In order to address some of the limitations and extend the findings of this study, future research efforts could aim to explore the effects of cultural influences on customers' perceptions and expectations of the shopping environment (Grewal et al., 2003; Turley & Milliman, 2000). The direct application of insights gleaned from studies conducted outside

China without careful consideration of the cultural context might produce undesirable results. Thus, it is important to rule out cultural differences when interpreting the concepts of cognition and emotion. This study is undoubtedly a starting point in exploring the appropriate use of store atmospherics in Chinese retail settings.

The search for the right type of AI-induced music system should also consider music familiarity, as familiar music may trigger unintentional emotions for which the customers are not prepared. As a result, such emotions could be heightened initially in response to a familiar tune, but annoyance or irritation could kick in shortly after the initial surprise has passed. Prior research has found differences in waiting time estimations when listening to familiar or unfamiliar music in a hypothetical retail setting (Yalch & Spangenberg, 2000). Unfamiliar music can slow down shoppers' perceptions of time (Yalch & Spangenberg, 1988), leading to undesirable outcomes for retailers for which waiting time is already a cause for concern.

Future research could focus on identifying other emotional factors (e.g., pleasure, arousal, dominance; Mehrabian & Russell, 1974). Also, research could measure cognitive activity using more objective measures, such as the number of thoughts and the depth of information processing (see Chebat et al., 2001). It would also be useful to adopt an objective measure of time perception (e.g., between actual and perceived waiting time) as a moderator in assessing the impact of music on cognition and emotion to complement self-reported measures (Oakes & North, 2008b). The current study could be replicated in a similar or an alternative purchasing context (e.g., hedonic and low-involvement products) with a view to establishing the robustness of the current findings. In addition, the effects of different musical elements, such as tempo or volume, should be further investigated to gain a richer understanding of how customers respond to them in various AI-induced purchasing scenarios. Further, we propose a comparative cross-cultural analysis for future studies (see Ferraris, Giudice, Grandhi, & Cillo, 2019). Finally, our findings for purchase intention and purchase behavior were not directly tested in the survey, and this should be explored in future studies.

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Figure 1: Facial Recognition → Music Recognition

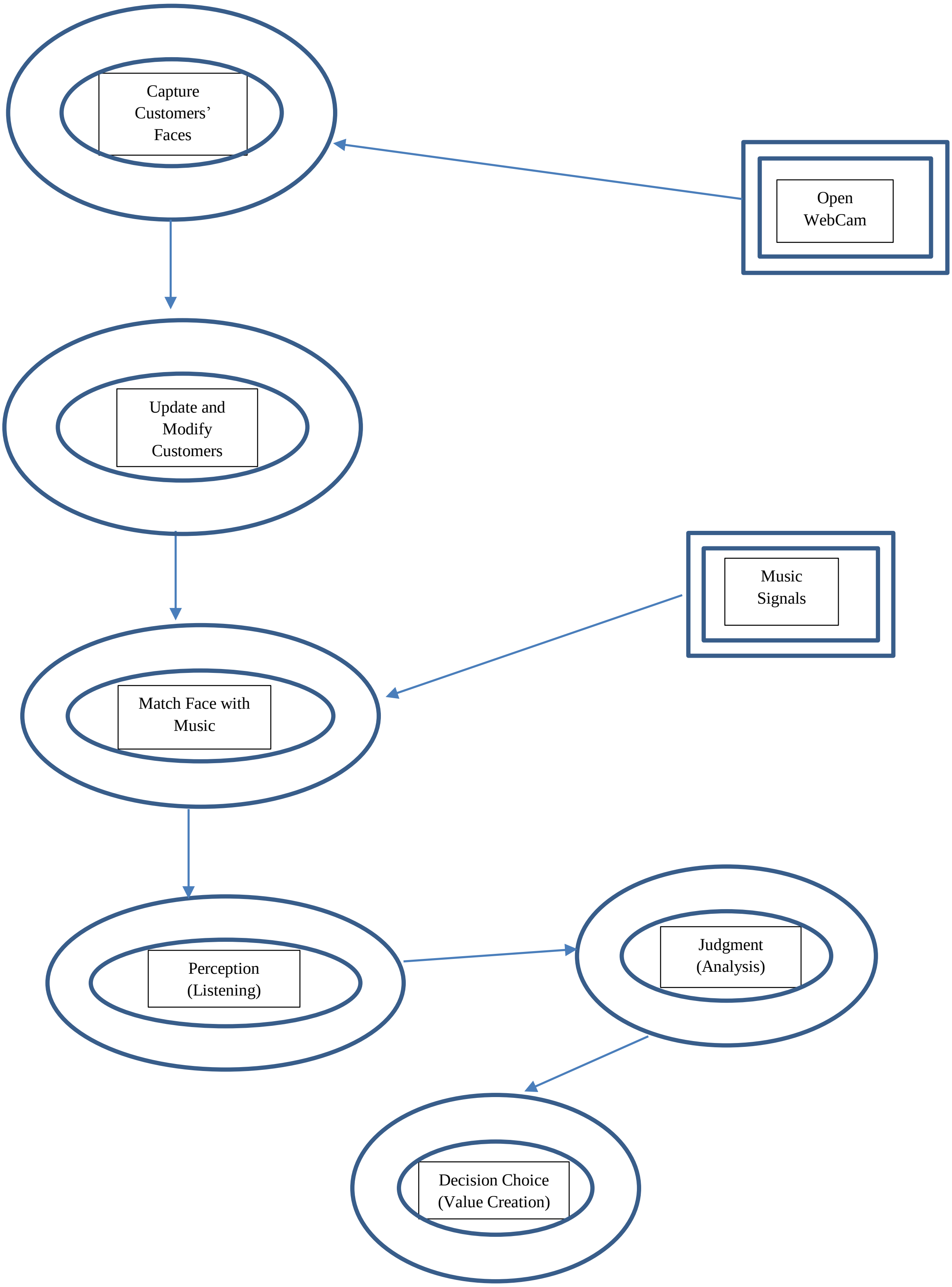
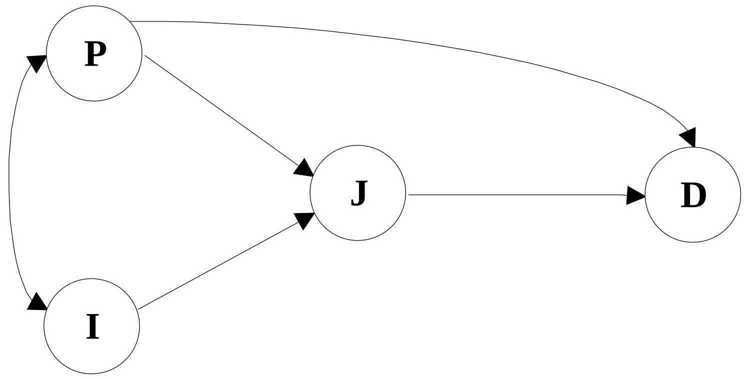


Figure 2. TP model diagram



Note. P = perception, I = information, J = judgment, and D = decision choice.

Perception

1. I truly enjoyed coming to the store.
2. I find the store setting stressful.
3. I find the store setting tense.
4. I find the store setting rushed.

Information

1. Age
2. Gender
3. Day of the experiment (presence of liked, disliked, slow-tempo, fast-tempo music or no music)

Judgment

1. I was irritated with the wait.
2. I was dissatisfied with the wait.
3. I felt frustrated with the wait.

Decision Choice

1. My decision to come to this store is wise.
2. I will recommend the store to my relatives and friends.
3. I am satisfied with the services provided by the store.
4. I like coming to the store (happy to visit).

Table 1. Summary of variables

Day	*Music manipulation*	*N respondents*
1	Liked	80
2	Disliked	78
3	Slow tempo	80
4	Fast tempo	80
5	No music	68

Table 2. Overview of experimental conditions

	Day 1 Liked music like (*N* = 80)		**Day 2 Disliked music (*N* = 78)**		**Day 3 Slow-tempo music (*N* = 80)**		**Day 4 Fast-tempo music (*N* = 80)**		**Day 5 No music (*N* = 68)**	
	M	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***
Perception	6.70	.636	6.71	.428	6.90	.252	4.87	1.166	6.89	.268

Table 3. ANOVA

(*N* = 373)	Component		
	Perception	**Judgment**	**Decision**
I truly enjoyed coming to the store (good environment).*	**.827**		
I find the store setting stressful.	**.761**		
I find the store setting tense.	**.752**		
I find the store setting rushed.	**.727**		
I was irritated with the wait (anxious, unsettled).		**.861**	
I was dissatisfied with the wait.		**.860**	
I felt frustrated with the wait (long waiting time).		**.859**	
My decision to come to this store is wise.			**.844**
I will recommend the store to my relatives and friends.			**.836**
I am satisfied with the services provided by the store.			**.795**
I like coming to the store (happy to visit).			**.791**
Cronbach's Alpha	.875	.965	.868

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
**Reverse-coding was used in the analysis.*

Table 4. Exploratory factor analysis

Perception and Information Interactional Effects

	Perception
Information--AGE	0.03**
Information—MUSIC DAYS	0.10*

Consumers' Decision Processes

Regression Weights[1]

Perception→Judgment

$\gamma_{\boldsymbol{PJ}}$ 0.65*

Information--AGE→Judgment

$\gamma_{\boldsymbol{AJ}}$ 0.02

Information—MUSIC DAYS→Judgment

$\gamma_{\boldsymbol{MJ}}$ 0.05

Perception→Decision

$\gamma_{\boldsymbol{PD}}$ 0.09

Judgment→Decision

$\gamma_{\boldsymbol{JD}}$ 0.65*

[1]Where ***P***-Perception, ***I***-***A***-Information-AGE, ***M***-Information-Music Days, ***J***-Judgment, ***D***-Decision Choice.[2]

**p* < .01. ***p* < .05.

Table 5. Causal model parameters

		Mean	*SD*	1	2	3	4	5	6	7	8	9	10	11
1	I truly enjoyed coming to the store.	6.55	0.951	1										
2	I find the store setting stressful.	6.32	1.179	.703**	1									
3	I find the store setting tense.	6.32	1.208	.673**	.927**	1								
4	I will recommend the store to my relatives and friends.	6.05	1.437	.493**	.455**	.461**	1							
5	I am irritated by the wait.	5.74	1.249	.477**	.647**	.637**	.372**	1						
6	I am dissatisfied with the wait.	5.68	1.270	.433**	.621**	.608**	.385**	.932**	1					
7	I feel frustrated with the wait.	5.75	1.210	.494**	.684**	.675**	.376**	.903**	.894**	1				
8	My decision to come to this store is wise.	6.45	0.772	.179**	.263**	.297**	.222**	.423**	.429**	.349**	1			
9	I will recommend the store to my relatives and friends.	6.46	0.722	0.075	.161**	.157**	.196**	.398**	.393**	.323**	.748**	1		
10	I am satisfied with the services provided by the store.	6.27	0.774	.216**	.258**	.252**	.239**	.431**	.451**	.416**	.590**	.533**	1	
11	I like coming to the store.	6.30	0.812	.346**	.368**	.357**	.357**	.512**	.499**	.493**	.629**	.564**	.730**	1

*** Correlation is significant at the 0.01 level (2-tailed)*

Table 6. Correlation matrix along with means and standard deviations