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When I am Sad, I Don’t Like AI: Preference for Music Playlists Curated by AI

Jieun Koo†

Associate Professor, Div. of International Commerce, Pukyong National University

Empathy is no longer the preserve of humans. As artificial intelligence (AI) becomes ubiquitous in consumers’ daily lives, they tend to favor AI that can read, understand, and resonate with their emotions. To broaden the understanding of how consumers perceive AI, this research explores the relationship between emotional valence and the perception of AI’s empathy, specifically in the context of music streaming services. The results of three experiments demonstrate two important findings. First, consumers believe that an AI music curator is less able to empathize with listeners’ negative emotions than positive ones. Second, due to this biased belief, they prefer AI-curated playlists made for negative mood less than those made for positive mood. These results provide insights into how to design and complement empathetic AI, particularly in the domains where sensitivity to users’ emotions is vital.

Key words : artificial intelligence, emotion, empathy, music, negativity bias, valence

† Corresponding Author : Jieun Koo, Associate Professor, Div. of International Commerce, Pukyong National University, jieunkoo@pknu.ac.kr

The popularity of artificial intelligence (AI) has risen dramatically, as shown by promising forecasts: AI's global market size is expected to reach USD 360 billion by 2028, with a compound annual growth rate (CAGR) of 33.6% ranging from 2021 to 2028 (Fortune Business Insight, 2021). Not only the number but also the variety of industries incorporating AI has grown rapidly and includes medical care, manufacturing, consumer services, farming, and education. Furthermore, the broad adoption acts as a catalyst to accelerate the advancement of AI technology, and hence the list of new areas that AI challenges continues to grow.

Enabling AI to respond appropriately to human's emotions is one of these new areas. As human-AI interactions have become common in everyday life, AI must be equipped with empathy to have frictionless communications with human users (Forbes, 2019). Business players invest their resources to enhance AI's empathetic ability to read, understand, and respond to human emotions. One example of this is affective computing. This is an interdisciplinary field involving psychology, computer science, and biomedical engineering whose motivation is to develop systems or devices to automatically recognize, model, and express emotions (Marin-Morales et al., 2018). According to Grand View Research (2020), affective computing's global market size was valued at USD 20 billion in 2019 and its expected CAGR is 33.0% from 2020 to 2027. Academic research is keeping pace with the market trend by exploring AI's empathy. Previous studies have demonstrated that empathetic AI improves consumers' experiences with AI-involved services and identified antecedents to increase the perceived empathy of AI (Niculescu et al., 2013; Pelau, Dabija, & Ene, 2021; Yoon & Lee, 2021).

The current research investigates AI's empathy from a different angle in the context of music streaming services. Specifically, we propose positive-negative emotion asymmetry in the perception of AI empathy. That is, consumers believe that AI is less able to empathize with negative emotions than positive emotions. As a result, consumers evaluate AI-curated music playlists made for negative emotions less favorably than ones made for positive emotions. These hypotheses rely on a cognitive complex representation of negative emotions, which is caused by the greater information value of negative stimuli compared to positive stimuli (Baumeister et al., 2001; Ducette & Soucar, 1974).

Given the growing importance of the emotional intelligence of AI, a basic understanding of how human users perceive AI's empathy is necessary to guide the technological and marketing efforts of AI companies. The findings of the current research imply that negative emotions need more sophisticated processing treatments and marketing messages. Our research also sheds light on the role of AI in the music industry. Recently, major music streaming services (e.g., Spotify) have actively deployed AI curators, but there is little research on how AI's suggestions are experienced by listeners. Considering that music choices are especially sensitive to listeners' emotions, our findings can enrich the insight about AI and its role in the arts sector.

Theory and Hypotheses

Empathy and AI

Empathy is broadly defined as the process of detecting, understanding, and feeling what another person is experiencing (Eerola et al., 2018). Similarly, empathy refers to an "affective response that stems from the apprehension of another's emotional state or condition and that is identical or very similar to what the other person is feeling or would be expected to feel" (Eisenberg, Wentzel, & Harris, 1998, p. 507). Although many discussions revolve around the empathy construct, many researchers agree that empathy has both cognitive and affective components (Davis, 1983; Simon, 2013). The cognitive component is the ability to comprehend the thoughts and feelings of others, referred to as perspective taking. The affective component allows individuals to vicariously experience others' feelings, leading to empathic concern and emotional contagion (Wieseke, Geigenmüller, & Kraus, 2012).

Empathy is considered central to human-to-human interaction, but AI is also required to embody empathy as the number of human-AI interactions increase rapidly in consumers' everyday lives. For example, AI interacts with consumers to provide personalized recommendations (Castelo, Bos, & Lehmann, 2019), medical care (Longoni, Bonezzi, & Morewedge, 2019), customer service (Adam, Wessel, & Benlian, 2021), and personal assistance (Hsieh & Lee, 2021) in the forms of recommendation agents, robots, chatbots, and smart speakers, respectively. One of the antecedents to transform such interactions into favorable consumer responses is AI's empathy. For instance, a greater perception of AI's empathy leads consumers to accept AI's recommendations more willingly (Yoon & Lee, 2021) and to trust AI agents more (Pelau, Dabija, & Ene, 2021). In a similar vein, interacting with an empathetic robot character is perceived to be easier (Niculescu et al., 2013), and empathy is considered the most critical aspect in developing nurse robots (Pepito et al., 2020).

Reflecting the importance of empathy in human-AI interactions, several studies have identified factors that enhance perceived empathy. The quality of the technology and personalization of AI recommendation services significantly affect empathy perception (Yoon & Lee, 2021). The anthropomorphic characteristics of an AI device also result in higher perceived empathy (Pelau, Dabija, & Ene, 2021). While these studies disclose meaningful information about consumers' perception of AI's empathy, many questions remain unanswered. The current research investigates one of the unanswered questions: Do consumers perceive that their every emotion is equally understood and shared by AI?

We propose that the perception of AI's empathy depends on emotional valence. Specifically, consumers believe that AI is less able to empathize with their negative emotions than positive emotions. This hypothesis is based on the concept of negativity bias and we review the relevant research in the following section.

Negativity Bias

People tend to give more weight to negative stimuli than to equally intense positive stimuli. This asymmetry is termed negativity bias (Baumeister et al., 2001; Peeters & Czapinski, 1990). Plentiful evidence has been reported in various domains. According to prospect theory (Kahneman & Tversky, 1979), the impact of loss is greater than that of gain in decision making, and this tendency is labeled loss aversion. Impression formation is also biased by negative information. Negative adjectives describing a hypothetical person are disproportionately more influential in arriving at a final impression than positive traits of comparable magnitude (Fiske, 1980). Learning is another domain where negativity bias manifests. Both humans and animals learn faster and their learning lasts longer when negative events are involved than positive events (Rozin & Royzman, 2001).

Neuroscience also produces evidence for a negativity bias. Yeung and Sanfey (2004) recorded undergraduate students' event-related brain potential (ERPs) as they played a simple game involving monetary gains or losses. They found that the feedback-related negativity (FRN) amplitude, one of the ERP components that typically responds to the outcomes of behaviors, was greater after losses than after gains. That is, FRN was more sensitive to negative than positive outcomes. Late positive potential (LPP), another element of ERP, showed a similar pattern in Ito et al. (1998): LPP amplitude was larger when participants were exposed to negative pictures than equally probable, extreme, and arousing positive pictures.

Along with the evidence for a negativity bias, prior literature has investigated what mechanisms underlie the bias. One mechanism is suggested by the range-frequency theory (De Haan et al., 2004). This theory explains that negative events are more surprising and unexpected because people perceive that the default value of most events surrounding them is positive (Klar & Giladi, 1997). Thus, negative events stand out and seem to convey valuable information worthy of greater attention and weight (Vaish, Grossmann, & Woodward, 2008). De Haan et al. (2004) investigated the range-frequency hypothesis with 7-month-old babies and found that the infants who experienced frequent positive interactions with their caregivers looked longer at fearful than happy facial expressions, which indicates a negativity bias. The second mechanism is that the evolutionarily adaptive purpose causes a negativity bias (Cacioppo et al., 1999). The consequences would be much more critical when an organism ignores harmful or damaging events than when it misses a good opportunity. Thus the process of natural selection may favor species with the propensity to react more strongly to negative events than positive events, which results in a negativity bias (Vaish, Grossmann, & Woodward, 2008).

Taken together, previous literature features abundant evidence that human beings display a negativity bias, and the root of that bias is that negative stimuli entail more diagnostic information about environments or objects than positive stimuli. In the following section, we review the consequences of a negativity bias.

Negative Emotions and AI's Empathy

Since negative stimuli have greater information value than positive ones, they lead to more cognitive work (Peeters & Czapinski, 1990). For example, what would you do if your colleague seems happy? Probably nothing. You would leave them alone because there is nothing to fix about their happiness. In contrast, what if your colleague seems annoyed? You would reflect on your verbal or behavioral interactions with the colleague today to discern which one hurt them. In addition, you would try to come up with an idea to change the colleague's mood. As in this example, negative stimuli work as a call for mental or behavioral adjustment, whereas positive stimuli do not call for such adjustments.

Numerous empirical studies have supported that negative stimuli demand such higher cognitive processing. For example, individuals looked at negative information longer than positive information, indicating greater attention (Fiske, 1980). Mental processing such as causal attribution also occurs more frequently for negative events (e.g., failing an exam) than for positive ones (e.g., passing an exam; see Weiner, 1985 for a review). Children display the same pattern. Compared with positive experiences, children who had negative experiences ruminate on their internal thoughts and feelings more and describe them more coherently to create meaning out of the chaotic experiences (Fivush et al., 2003). Children's conversations with parents about negative emotions are also more elaborated. They discuss the causes of emotions and ask open-ended questions more frequently. They also use a more extensive vocabulary of emotional words during a discourse about negative feelings (Lagattuta & Wellman, 2002). Furthermore, negative emotions promote more careful and systematic information processing, consequently leading to more accurate judgments (Fiedler & Bless, 2000). Even persuasive messages created by people in negative mood are perceived as more concrete and thus induce greater attitude change (Forgas, 2007).

Drawing on these results, we propose that negative emotions are perceived as more complicated and profound than positive ones. As discussed above, negative stimuli demand more elaborated processing, and this marked character develops into a more complex cognitive representation of negative stimuli. For example, when evaluating randomly generated shapes, people perceive disliked shapes as more complex than liked ones (Ducette & Soucar, 1974). The perception of other people's complexity also increases when individuals perceive the person in a negative way (Miller & Bieri, 1965). Similarly, the perceived heterogeneity of disliked groups was stronger (i.e., less homogeneous) than that of liked groups (Koenig, 1999). That is, disliked groups were perceived as having more complex member composition. The association between negativity and complexity has been reported even more various domains. For example, perceived complexity is greater for negatively evaluated products than positively evaluated ones (Pinson, Malhotra, & Jain, 1984). When judging occupations, participants utilized more cognitive constructs (i.e., greater complexity) for disliked occupations than liked ones (Bodden & Klein, 1973). Therefore we expect the same effect for emotions, namely, that negative emotions are perceived as more complicated and multifaceted than positive emotions.

We contend that the complexity of negative emotions results in the belief that AI has more difficulty in understanding negative emotions than positive ones. Consequently, consumers would infer that AI is less able to empathize with their negative emotions. It is a common sense that one cannot empathize with the emotions that they don't understand. Also in the lab, people experiencing emotional processing disturbances show empathy deficit (de Sousa et al., 2010). Thus negative emotions' complexity and AI's inability to process it lead people to believe that AI's empathy with negative emotions is weak.

Furthermore, the lower perception of AI's empathy decreases preference for offers from AI. Consumers are less inclined to comply with suggestions made by unempathetic service providers (Adam, Wessel, & Benlian, 2021; Simon, 2013; Yoon & Lee, 2021). Therefore, listeners would evaluate AI-curated playlists for negative mood less favorably because they believe that an unempathetic AI has made the playlists. In sum, negative stimuli call for greater cognitive work and thus have more complex cognitive representations (Peeters & Czapinski, 1990). This infuses consumers with the belief that AI's empathy with negative emotions is weaker than with positive emotions, consequently lowering preference for AI-curated playlists made for negative mood.

Based on this rationale, we propose the following hypotheses:

H1: People believe that AI is less able to empathize with negative emotions than positive emotions.

H2: People prefer AI-curated playlists less when those are offered for negative emotions compared for positive emotions.

H3: The lower preference for AI-curated playlists for negative emotions is mediated by the belief that AI is incompetent at empathizing with negative emotions.

Pretest

A pretest examined whether negative emotions are perceived as more complicated and profound than positive ones. A total of 101 participants (64% female, M_{age} = 39.2) were recruited via Prolific. First, participants rated the complicatedness of negative emotion on three 7-point Likert scales ("*Negative emotions, such as sad, frustrated, distressed, gloomy, angry, etc., are complicated / profound / deep*."; 1 = *completely disagree*, 7 = *completely agree*; α = .85). Then they rated positive emotion in the same way ("*Positive emotions, such as happy, pleased, satisfied, relaxed, excited, etc., are complicated / profound / deep.*"; α = .71). We provided examples of each emotional valence to avoid vagueness or ambiguity of questions. The repeated ANOVA showed that participants perceived negative emotions as being more complex than positive emotions ($M_{positive}$ = 3.93 vs. $M_{negative}$ = 4.98, $F(1, 100) = 42.12$, $p < .001$).

Study 1

Study 1 tested H1 that people believe that AI is less able to empathize with negative emotions than positive emotions. To this end, we created scenarios in which an individual listens to music playlists curated by AI or humans on a perfect or terrible day. After reading the scenario, participants answered questions about their perceptions of the curator's empathy.

Method

A total of 360 participants (58% female, M_{age} = 30.2) were recruited via Prolific to participate in a 2 (valence: positive vs. negative) × 2 (curator: AI vs. human) between-subjects experiment. The positive (negative) condition asked participants to imagine using a music app on a perfect (terrible) day, and the AI (human) condition described the playlists curator as AI (artists and listeners). The human condition was included to show that the lay belief about poor negative empathy manifests only in the AI condition. The specific scenarios are presented below:

<Positive valence & AI curator>

"Imagine that you have a perfect day. When you woke up, it was bright and sunny outside. On the way to work, there was no traffic jam. In the afternoon, your important client finally signed the contract that you have been working on for a long time. Your boss praised your accomplishment in front of other colleagues.

On the way home, you want to listen to the right songs for your mood on a perfect day. So you open the music app on your smartphone, and the app recommends several playlists curated by AI (artificial intelligence). Those have a good review rating (earned 4 stars on a 5-star rating system) by other users of the music app. "

<Negative valence & human curator>

"Imagine that you have a terrible day. When you woke up, it was gloomy and rainy outside. On the way to work, there was a heavy traffic jam. In the afternoon, your important client broke the contract that you have been working on for a long time. Your boss criticized your failure in front of other colleagues.

On the way home, you want to listen to the right songs for your mood on a terrible day. So you open the music app on your smartphone, and the app recommends several playlists curated by artists or listeners. Those have a good review rating (earned 4 stars on a 5-star rating system) by other users of the music app. "

After reading the scenario, participants judged the degree to which the curator empathizes with their emotions on three 7-point Likert scales (items adapted from Andreychik & Migliaccio, 2015; Kellett, Humphrey, & Sleeth, 2006; "[*AI*] *can empathize with what you feel on a* [*perfect*] *day*," "[*AI*] *can tune into the emotions you experience on a* [*perfect*] *day*," "[*AI*] *can share the feelings that you have on a* [*perfect*] *day*."; 1 = *completely disagree*, 7 = *completely agree*; α = .91). The text inside of brackets was different according to the assigned condition. Then participants answered the manipulation check questions by reporting the emotions they might feel on the perfect or terrible day with two 7-point items (*negative-positive, unpleasant-pleasant*; α = .98).

Results and Discussion

Manipulation check. A two-way (valence × curator) ANOVA on the emotion yielded a significant main effect of the valence ($F(1, 356) = 1192.67$, $p < .001$), but the other effects were not significant ($ps > .475$). This means that the perfect day scenario in the positive condition induced more pleasant emotion than the terrible day scenario in the negative condition ($M_{positive} = 6.66$ vs. $M_{negative} = 2.24$). Thus the manipulation was successful.

Empathy with emotion. A two-way (valence × curator) ANOVA on the perception of the curator's empathy demonstrated a significant main effect of curator ($F(1, 356) = 118.60$, p

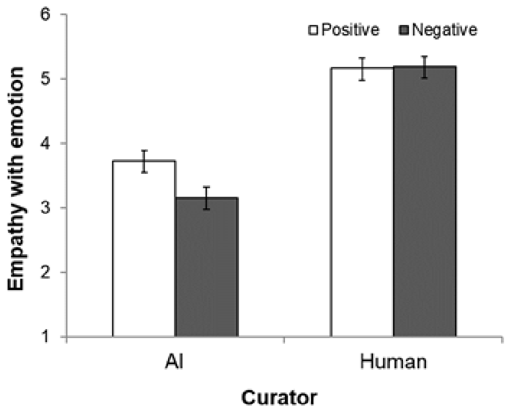

Figure 1. Effects of curator and emotional valence on empathy judgement in Study 1.

$< .001$), a marginally significant main effect of valence ($F(1, 356) = 2.99$, $p = .085$), and a marginally significant interaction effect ($F(1, 356) = 3.62$, $p = .058$). The main effects of curator and valence indicated that the curator’s empathy was perceived to be higher when the curator was human than AI ($M_{human} = 5.17$ vs. $M_{AI} = 3.45$) and when the valence was positive than negative ($M_{positive} = 4.45$ vs. $M_{negative} = 4.17$). More importantly, we analyzed the two-way interaction by using cell mean contrasts (Figure 1). In the AI condition, the empathy perception decreased when participants had negative emotions compared with positive emotions ($M_{positive} = 3.73$ vs. $M_{negative} = 3.16$; $F(1, 356) = 6.56$, $p = .011$). However, the empathy perception did not significantly differ in the human condition ($M_{positive} = 5.16$ vs. $M_{negative} = 5.19$; $F(1, 356) = .02$, $p = .900$). These results supported H1.

As expected, participants believed that AI could not understand negative emotions as much as positive emotions, but this lay belief does not apply to human curators. Interpersonal emotion regulation can explain the lay belief’s disappearance in the human condition. Human dampens, intensifies, or maintains both positive and negative emotions not only by themselves but also by sharing with others (Rimé, 2007). Specifically, by social sharing, positive emotions are prolonged whereas negative emotions are overcome. Such interpersonal emotion regulation is so common in our daily lives that negative empathy is as usual as positive empathy. Thus the empathy perception did not show a significant difference across emotional valence in the human condition.

Study 2 examined the consequence of the lay belief. We expect that individuals feeling negative (vs. positive) emotions prefer AI-curated playlists less because the idea of AI’s low negative empathy might lead to the prejudice that its song curation is poor.

Study 2

Study 2 had two purposes. First, we tested H2 that preference for AI-curated playlists decreases when listeners feel negative emotions compared with positive emotions. Second, we attempted to show that the decreasing preference is caused by the belief that AI lacks the ability to empathize with negative emotions. When a music curator cannot understand listeners' emotions, it is reasonable to judge that the curator's music selection is not satisfactory, which results in a low preference for the curator's playlists.

Method

A total of 299 participants (54% female, M_{age} = 33.2) recruited from Prolific participated in a one-way between-subjects experiment that manipulated emotional valence (positive vs. negative). The scenario to manipulate emotional valence was similar to that in Study1. Specifically, the first paragraph (i.e., the description of a perfect or terrible day) was the same as in Study 1, but the second paragraph was different, saying that the music app recommended two playlists, one curated by a human and one by AI. The new second paragraph of the positive condition is reproduced below (the word inside of the bracket was "*terrible*" in the negative condition):

<The second paragraph in the positive condition>

"*On the way home, you want to listen to the right songs for your mood on a {perfect} day. So you open the music app on your smartphone, and the app recommends two playlists, one curated by a human and the other curated by AI (artificial intelligence). Both playlists have an equal review rating by other users of the music app.* "

After reading the perfect or terrible day scenario, participants indicated which playlist they would prefer on a 7-point scale (1 = *definitely a playlist curated by a human*, 7 = *definitely a playlist curated by AI*). Then they answered the manipulation check questions (α = .99) as in Study 1.

Subsequently, the mediator was measured with the items used in Study 1 but modified slightly. Specifically, participants judged the degree to which AI can empathize with their emotions on three 7-point Likert scales ("*AI can empathize with what you feel on a perfect (terrible) day as much as a human can do*," "*AI can tune into the emotions you experience on a perfect (terrible) day as much as a human can do*," "*AI can share the feelings that you have on a perfect (terrible) day as much as a human can do*."; 1 = *completely disagree*, 7 = *completely agree*; α = .90).

Last, we measured participants' perceived control to rule out an alternative explanation. According to Horswill and McKenna (1999), individuals who feel in control are more comfortable with risk-taking behaviors than those who do not. One can argue that the terrible day scenario decreases perceived control. Consequently, participants in the negative condition may hesitate to choose AI-curated playlists because new technology (i.e., AI) is always riskier than traditional approaches (i.e., humans). To eliminate this explanation, participants reported their perceived control on two 7-point Likert scales ("*I have a great deal of control over the perfect (terrible) day*," "*The perfect (terrible) day is completely under my control*."; 1 = *completely disagree*, 7 = *completely agree*; α = .87).

Results and Discussion

Manipulation check. The manipulation was successful. The perfect day scenario in the positive condition induced more pleasant emotion than the terrible day scenario in the negative emotion condition ($M_{positive}$ = 6.73 vs. $M_{negative}$ = 1.81, $F(1, 297) = 1673.78$, $p < .001$).

AI's empathy with emotion compared with a human. Consistent with our expectation, participants perceived that AI's empathic understanding compared with a human was lower when emotional valence was negative than positive ($M_{positive}$ = 2.91 vs. $M_{negative}$ = 2.45, $F(1, 297) = 7.17$, $p = .008$) (Figure 2A). This result cohered with Study 1.

Preference for playlists. Preference for an AI-curated playlist decreased when emotional valence was negative compared with positive ($M_{positive}$ = 3.36 vs. $M_{negative}$ = 2.97, $F(1, 297) = 4.14$, $p = .043$; see Figure 2B). This result supported H2.

Mediation test. We ran a mediation test with AI's empathy as a mediator. Zhao, Lynch, and Chen's (2010) method (Hayes Model 4, 95% CI, 5000 samples) yielded a significant indirect effect (indirect effect = −.1882, CI[−.3611, −.0452]), but the direct effect was not significant (direct effect = −.2054, CI[−.5651, .1543]). This result provided evidence for H3.

Alternative explanation. We examined the relationship between emotional valence and perceived control. The analysis showed that participants in the negative condition perceived lower control than those in the positive condition ($M_{positive}$ = 3.84 vs. $M_{negative}$ = 3.34, $F(1, 297) = 7.97$, $p = .005$). Next, we

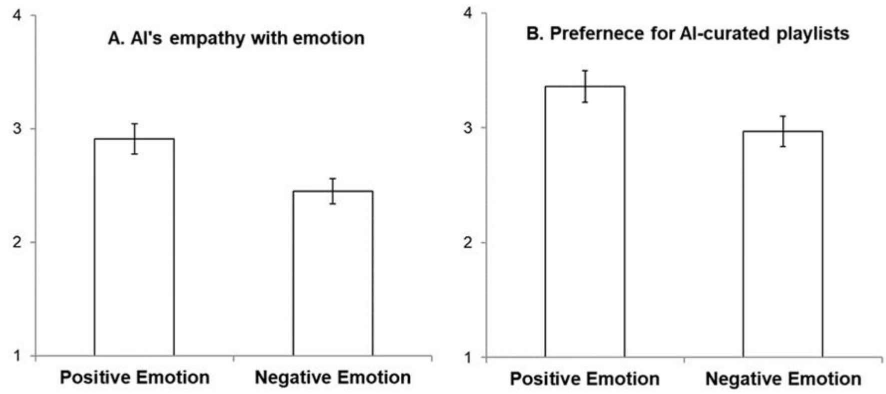

Figure 2. Effect of emotional valence on empathy judgement and playlist preference in Study 2.

analyzed the effect of emotional valence on preference for AI-curated playlists, including perceived control as a covariate. The results showed that perceived control was not a significant covariate (p = .208) and the effect of emotional valence remained marginally significant (p = .072). We also examined the mediating effect of perceived control using Zhao, Lynch, and Chen's (2010) method (Hayes Model 4, 95% CI, 5000 samples). The results revealed that the indirect effect was not significant (indirect effect = −.0400, CI[−.1421, .0317]), indicating that perceived control did not cause the difference in preference for AI-curated playlists. Thus, we can rule out the alternative explanation based on perceived control.

In Study 3, we tested the effect in a different context. This attempt can increase the generalizability of the current research.

Study 3

Study 3 attempted to examine the robustness of the relationship between emotional valence and preference for AI-curated playlists. The bottom line of the effect is that AI is perceived as inept at selecting songs for negative emotions compared with positive emotions. If this is the case, when a digital music service provides only AI-curated playlists, consumers would be less likely to use the service when they feel negative emotions. Another purpose of Study 3 was to eliminate an alternative account that an adverse and pessimistic attitude caused by negative emotion can explain the current effect. Serving this purpose, Study 3 did not manipulate emotional valence unlike Studies 1 and 2.

Method

A total of 200 participants (64% female, M_{age} = 35.7) recruited via Prolific were randomly assigned to either the human or AI condition. In the human (AI) condition, participants were told to imagine that they had logged into a digital music service providing access to many playlists made by artists worldwide (by AI). Appendix A includes the stimuli. Then participants reported when they wanted to listen to the playlists. They chose three emotions out of four positive (when happy, pleased, satisfied, and relaxed) and four negative emotions (when frustrated, distressed, sad, and gloomy). Note that frustrated, distressed, sad, and gloomy are the counterparts of happy, pleased, satisfied, and relaxed in terms of valence, respectively. That is, frustrated and happy, for example, are the opposite in terms of valence but similar in degree of arousal (Russell, 1980).

Results and Discussion

A chi-square test showed that the number of

Table 1. Effect of curator on the number of positive emotions chosen by participants

		The number of positive emotions in three emotion choices			
		3	2	1	0
Curator	Human (n=100)	38%	42%	19%	1%
	AI (n=100)	52%	27%	16%	5%

Note. The number of 3 (0) means that participants selected only positive (negative) emotions.

positive emotions among the three emotion choices differed as a function of curator ($\chi^2(3, N = 200) = 8.36$, $p = .039$; Table 1). Follow-up tests revealed that the percentage of participants who only chose positive emotions was significantly higher in the AI condition (52%) than in the human condition (38%; $z = 1.99$, $p = .047$). On the contrary, the percentage of participants who included one negative emotion (i.e., two positive emotions) was significantly lower in AI condition (27%) than in the human condition (42%; $z = -2.23$, $p = .026$). These results imply that AI-curated playlists were perceived as more suitable for positive emotions than negative emotions, which is consistent with the results of our previous studies. The frequencies for one and zero positive emotion were not significantly different across the curators ($|z| < 1.65$, ps $> .100$).

General Discussion

The current research investigates positive-negative emotion asymmetry in the perception of AI empathy. In the context of music streaming services, we observed that an AI music curator is perceived as less capable of empathizing with negative emotions compared with positive ones. We also showed the consequence that the AI-curated playlists are less preferred when they are made for negative mood than positive mood.

In fact, AI is neutral to emotions. This technology does not differentiate positive emotions from negative ones and simply processes all emotions as 0 or 1. Thus, software developers have no reason to believe that AI is inferior at reading and comprehending negative emotions. This idea, unfortunately, turns out to contradict the psychology of ordinary people. Instead of considering AI algorithms as neutral tools, consumers tend to apply their psychological and behavioral habits to the 0-or-1 world. Therefore, failure to incorporate human beings’ inherent properties into AI technology may undermine consumers’ experiences with AI (Puntoni et al., 2021).

Our findings provide important theoretical implications. First, to our knowledge, the current study is the first to explore the effect of emotional valence on the perception of AI's empathy. Since empathy is resonance with other's emotions (Eerola et al., 2018) and valence is the significant dimension to define emotions (Russell, 1980), it is fundamental to ask whether the perceived empathy of AI varies with emotional valence. Thus, our findings contribute a meaningful insight to the literature on AI's empathy.

Second, our research expands the literature on negativity bias. The dominance of negative stimuli is so pervasive that we can find evidence in various fields ranging from history, religion, and culture to learning, attention, and moral judgment (Rozin & Royzman, 2001). However, few would expect that the bias is effective for judgments about AI, the most cutting-edge technology in this era. Our findings highlight the potency of negativity bias by showing its influence even in the most scientifically advanced domain such as AI.

Third, we found the shortcomings of using AI in music streaming services. Due to economic efficiency and powerful data processing, AI-based music curation is doubtlessly considered a perfect way to proceed. However, our findings suggest that consumers doubt AI's capability to empathize with emotions, especially negative ones, and this doubt can cause a devaluation of AI-made products or services.

This study also provides business implications. Managers of music streaming services need to recognize the low preference for AI-curated playlists, especially ones for negative mood. We recommend that companies increase human curators' participation in creating playlists for negative mood and actively communicate the curation policy to listeners. Furthermore, managers in arts-related industries can refer to the current research. AI is currently being used to compose music, draw paintings, and write novels and poems. Despite its immature stage, this technology is attractive enough to grab headlines. For AI art to move to the next stage, human audience's acceptance is critical, yet our findings raise the concern that AI art may be depreciated when it is related to negative emotions. Considering that negative emotions such as sadness, depression, fear, and anger are inspirational sources for art, the preconception that AI is inept at negative emotions can hinder AI art from gaining acceptance and being appreciated. Companies developing AI art need to design a course of action to overcome these potential shortcomings.

In spite of the implications, this study is subject to limitations that provide interesting avenues for future research. First, the current findings can be explained by an alternative account based on interpersonal emotional regulation. Individuals frequently use others' support as a resource to mitigate their negative mood. In this regard, an AI curator is not an appropriate resource because it is not a human. Therefore, consumers' responses to AI may be unfavorable when they feel a negative mood.

However, interpersonal emotional regulation also works for positive emotions because people intensify their positive affect by sharing it with other people (Zaki & Williams, 2013). Thus, interpersonal emotional regulation cannot explain negative emotion's asymmetrical decrease in AI empathy perception and playlist preference. Nevertheless, to decisively eliminate this alternative account, future researchers can attempt to test it by measuring or manipulating relevant constructs.

Second, the current investigation is confined to music curating. Future researchers should explore our hypotheses in other domains of art, such as painting. For example, the same painting whose theme is love or hate can be presented as the work of an AI or a human. If the same effect is observed, the current research can obtain generalizability.

Third, the boundary conditions of the current effect need to be addressed. Possible moderators include an individual's innovativeness, anthropomorphic tendency, and dispositional negativity. Also usage experience of AI may moderate the effect. For example, users (vs non-users) of an AI speaker are more likely to humanize AI due to the daily interactions with it, and thus the asymmetrical effect of emotional valence on AI empathy perception can diminish. In addition, product type may work as a boundary condition. Wien and Peluso (2021) showed that, for hedonic products, human recommenders caused higher purchase intention than AI recommenders but this difference lessened for utilitarian products. We expect that the similar pattern can emerge because emotion is more relevant for hedonic categories. Further research on these moderators can contribute new knowledge to this increasingly important topic.

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인공지능이 추천한 음악 플레이리스트 선호에 관한 연구: 사용자의 감정을 중심으로

구 지 은

부경대학교 국제통상학부 부교수

공감은 더 이상 인간의 전유물이 아니다. 인공지능이 우리의 일상생활에 보편화되면서 소비자는 자신들의 감정을 파악하고, 이해하고, 공감해 주는 인공지능을 선호하고 있다. 소비자가 인공지능을 어떻게 인식하는가에 대한 이해를 높이기 위해 본 연구는 소비자가 느끼는 감정가(emotional valence: 긍정 vs. 부정)에 따라 인공지능의 공감 능력에 대한 판단이 달라지는가를 음악 스트리밍 서비스 측면에서 살펴보았다. 세 개의 실증연구를 통해 두 개의 결과를 얻을 수 있었다. 첫째, 소비자는 음악 추천 인공지능이 사용자의 긍정적 감정 대비 부정적 감정에 대해 공감하는 능력이 떨어진다고 믿는다. 둘째, 이 왜곡된 믿음으로 인해 소비자는 인공지능이 긍정적 감정을 느끼는 사용자에게 추천한 음악 대비 부정적 감정을 느끼는 사용자에게 추천한 음악을 덜 선호하게 된다. 이 결과는 특히 사용자의 감정에 민감하게 반응해야 하는 산업에서 인공지능을 개발하고 활용할 때 의미있는 시사점을 제공한다.

주요어 : 인공지능, 감정, 공감, 음악, 부정 편향, 감정가

Appendix A: STIMULI (Study 3)

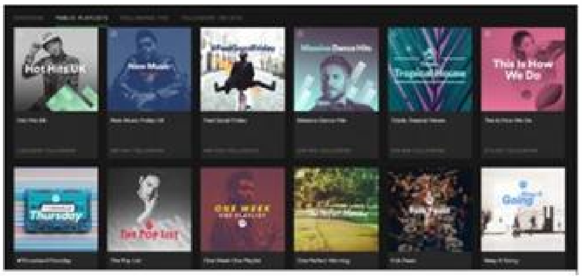
Human Condition

<Music playlist made by artists>

Imagine that you have just logged in to a digital music service.

This service has loads of **playlists made by artists** worldwide.

So you can find a perfect playlist whatever you want.



AI Condition

<Music playlist made by artificial intelligence>

Imagine that you have just logged in to a digital music service.

This service has loads of **playlists made by AI (artificial intelligence).**

So you can find a perfect playlist whatever you want.