Journal of Communication, 2023, **00**, 1–18
https://doi.org/10.1093/joc/jqad020
Original Article

International Communication Association

OXFORD

Computationally modeling mood management theory: a drift-diffusion model of people's preferential choice for valence and arousal in media

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Abstract

Mood management theory (MMT) hypothesizes that people select entertainment content to maintain affective homeostasis. However, this hypothesis lacks a formal quantification of each affective attributes' separate impact on an individual's media content selection, as well as an integrated cognitive mechanism explaining media selection. Here we present a computational decision-making model that mathematically formalizes this affective media decision-making process. We empirically tested this formalization with the drift-diffusion model using three decision-making experiments. Contrary to MMT, all three studies showed that people prefer negatively valenced and high-arousal media content and that prevailing mood does not shape media selection as predicted by MMT. We also discovered that people are less cautious when choices have larger valence differences. Our results support the proposed mathematical formalization of affective attributes' influence on media selection, challenge core predictions drawn from MMT, and introduce a new mechanism (response caution) for media selection.

Keywords: mood management theory, drift-diffusion model, computational modeling, open science

Why and how we select specific media has been a central question for media researchers since the 1940s. One of the prevailing theories explaining entertainment media selection is mood management theory (MMT; Zillmann, 1988).[1] MMT suggests that people's selective exposure to media content is determined by the media users' prevailing mood and the affective properties of media content, such that people choose media content that will help them maintain a moderate level of arousal (avoiding hypo- or hyper-arousal) and will change their prevailing mood state towards a positive direction. However, MMT research has mainly focused on behavioral tests of media choice or the effects of choice on mood (Carpentier, 2020; Reinecke, 2016); and empirical MMT research shows mixed support for key propositions of the theory (e.g., Knobloch-Westerwick, 2014; Strizhakova & Krcmar, 2007). Thus, despite sustained effort, it remains unclear how users' affective states influence their selection of specific media content. In fact, in our review of the literature, MMT only meets a few of the established criteria for evaluating a theory in communication (DeAndrea and Holbert, 2017). It is parsimonious, heuristically generative, and provides a clear organizing scheme in terms of selective exposure to media along specific dimensions. However, to date, the extent to which MMT offers explanatory power, falsifiability, and internal consistency is not well reflected in the literature.

We propose that computational modeling provides clarity into media selection processes and demonstrate how this approach can be applied to test hypotheses derived from MMT by making sense of observed behavioral media choice and response time (RT) data with precise mathematical models (Wilson & Collins, 2019). In three studies, we apply a computational decision-making model, the drift-diffusion model (DDM; Ratcliff and McKoon, 2008), to a two-choice (dichotomous) media selection task in order to investigate whether and how people's entertainment media choices are influenced by their prevailing mood and affective attributes of media. When using the DDM, people's value-based decision making, such as choosing a movie (e.g., comedy, drama), is assumed to be a continuous noisy preferential evidence accumulation process that drifts toward one of two possible decision boundaries (e.g., comedy or drama). Said differently, the DDM accounts for these observable media selection outcomes using choice and RT data. The DDM helps us better understand how affect influences people's media selection and contributes to theory by providing empirical evidence for or against the person- and content-specific mechanisms that influence media selection. Our study shows how to utilize such models to formalize and test a verbal theory, and demonstrates the theoretical value (DeAndrea & Holbert, 2017) of the approach by aiding in falsification, identification of boundary conditions, and identifying new mechanisms in existing communication theories.

Mood management theory

MMT, or the theory of affect-dependent stimulus arrangement (Zillmann, 1988), suggests that individuals are motivated to terminate noxious affective states by arranging their media environments in a way to "perpetuate and increase the intensity of gratifying, pleasurable excitable states" (p. 158). These arrangements can be grouped to form four primary hypotheses: (a) persons in aversive states will prefer hedonically

Received: 28 August 2022. **Revised:** 3 May 2023. **Accepted:** 3 May 2023

positive stimuli (valence hypothesis), (b) persons in states of extreme over- or under stimulation will act to return to a baseline (excitatory homeostasis), (c) persons in a noxious mood state will display a preference for the most absorbing types of stimulation to intervene in a prevailing mood state (intervention potential), and (d) persons will select stimuli with minimal behavioral affinity with their experiential state (semantic affinity). DDM is particularly well suited for addressing MMT's first two hypotheses.[2] Therefore, in what follows, we explicate linkages between DDM and MMT with regard to MMT's valence and excitatory homeostasis hypotheses.

The drift-diffusion model of decision making

The DDM (Ratcliff and McKoon, 2008) explains people's *preferential choice* and *response time* in speeded two-choice decision tasks. DDM suggests that a person's decision is the result of an evidence-accumulating process, where decision makers collect preferential evidence in favor of one option or another alternative, as a function of weighted attributes of the options (Figure 1A). The options in a two-choice decision task are represented as an upper decision boundary (α; the correct or high subjective value option) and a lower decision boundary (0; the error or low subjective value option). When the accumulation of evidence reaches either one of the choice boundaries, the decision-making process is complete. The drift process begins at a starting point (Z) in between the two choice boundaries which represents predecision bias. After accounting for non-decision time (T), the decision maker accumulates evidence or information that leads to a noisy drift process (v) toward the preferred choice boundary, following a signal detection model.

Computational parameters in the DDM have unique conceptual operationalizations. Specifically, *non-decision time* (T), accounts for perceptual processing and executing the decision; *decision boundaries* (α, 0), account for decision cautiousness, with wider boundaries representing more cautious decision making; *decision starting point* (Z), accounts for biased preferences before encountering the decision options; and *decision drift rate* (v), accounts for the rate of evidence accumulation or the subjective value difference between options. The decision drift rate sign indicates choice

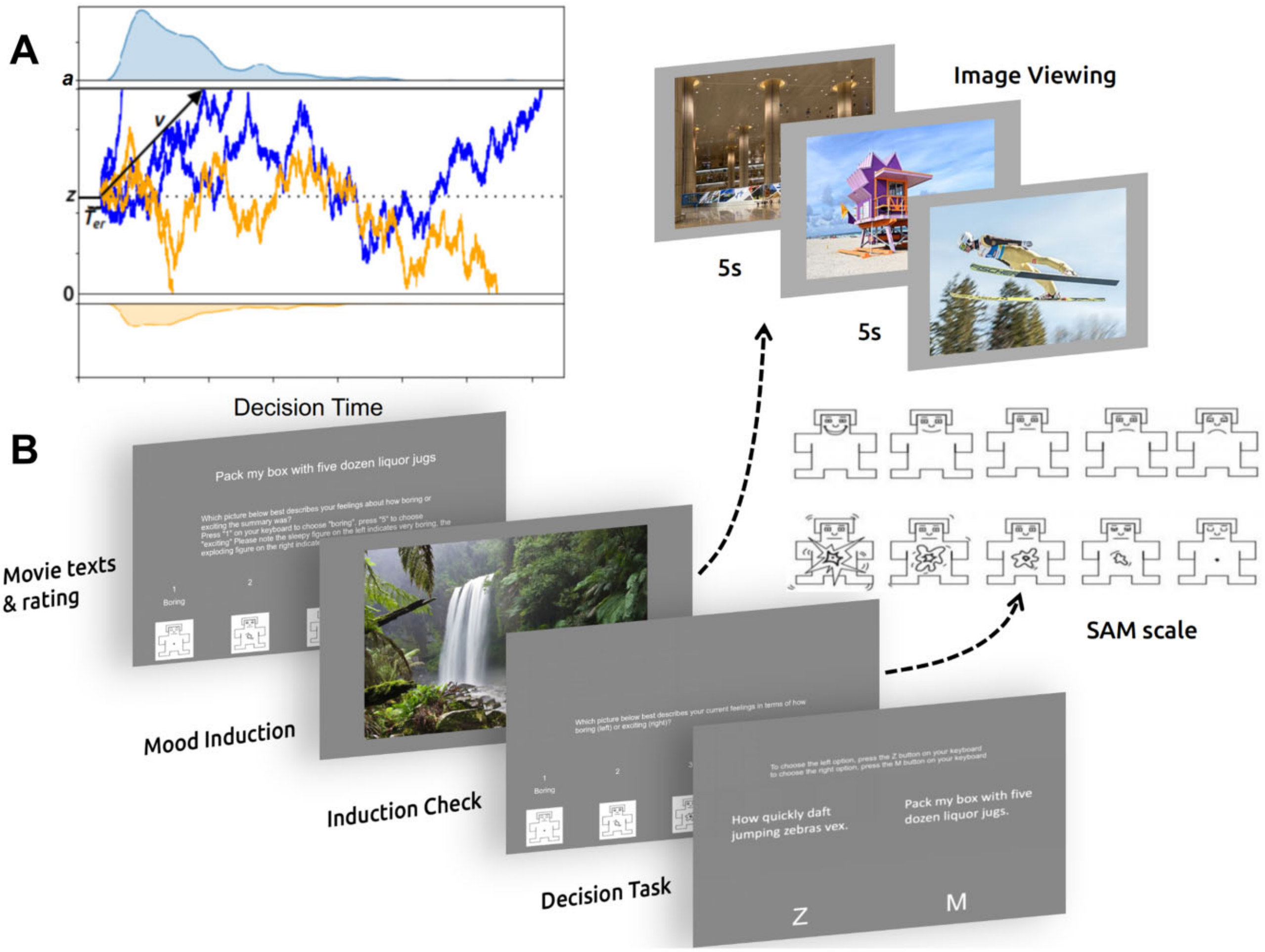

Figure 1 (**A**) The DDM. Choices in a decision task are represented as upper (α) and lower (0) boundaries. The drift process starts at a biased point (Z). Drift rate (v) follows a noisy drift toward the preferred choice. Non-decision time (T) is also estimated. The upper and lower panels show RT distributions. (**B**) Experimental procedure. For all studies, participants were shown movie texts and asked to rate the valence and arousal of the movie texts (training phase). In studies two and three only, participants were randomly assigned into one of four experimental mood induction (image viewing) conditions which included an induction check (prevailing mood rating was measured using the SAM). Lastly, for all studies, participants completed the decision tasks.

preference. Positive signs indicate a preference for the high-value (or correct) choice, negative signs indicate a preference for the low-value (or error) choice.

The DDM has been widely applied (Ratcliff et al., 2016) with emerging research focused on value-based decision making. Value-based decisions are when people make decisions based on a comparison of the subjective values of the choices, such as deciding what to eat (Krajbich et al., 2015), purchase (Krajbich et al., 2012), or who to socialize with (Krajbich et al., 2015).

During value-based decision making, decision makers construct object representations featuring attributes of each choice (Rangel et al., 2008). People then evaluate the subjective value for each attribute of the representations (Krajbich et al., 2010; Milosavljevic et al., 2010). Subjective value refers to the positive or negative value an individual assigns to an attribute, which is then weighted by how important that attribute is to the individual. The integrated subjective values for each choice are then compared. People's value-based decision making is mainly driven by subjective value differences between the choices, regardless of each choice's absolute value (Tajima et al., 2016). Therefore, the decision process takes longer for choices with small subjective value differences compared to choices with large subjective value differences. In other words, choosing between two apples should take longer than choosing between an apple and an orange.

Combining the DDM and MMT

Given that MMT hypothesizes that affective attributes of media content influence the expected subjective value of a media choice, media selection in the service of mood management can be considered a *value-based decision-making* task. Treating media selection as a value-based decision-making task is in line with literature suggesting that affect is information integrated into subjective value calculations for decision making (Greifeneder et al., 2011; Hartley et al., 2018; Roberts & Hutcherson, 2019; Schwarz, 2012; Shulman & Bullock, 2019). This perspective is also consistent with media scholars such as Knobloch-Westerwick (2014), who suggest that mood management via media can be fit to an expectancy-value framework, meaning that a linear relationship between affective attributes of media content and expected subjective value may ultimately determine media selection. Thus, we propose that media selection can be modeled as a multi-attribute value-based drift-diffusion process.

What does this mean? When given a two-choice decision task (choosing content A or content B), the direction and speed of evidence accumulation (which is directly related to drift rate) will be based on the subjective value difference between the media choices. Within a two-choice decision task, the affective attributes of choice A and B vary, as does the importance of these affective attributes for each individual. Jointly, and as discussed above, the subjective value difference between these attributes contributes to the choice. Two choices that have very similar attributes will have a small subjective value difference whereas two choices that have very dissimilar attributes will have a large subjective value difference. When subjective value differences are small, drift rate is low and selection approximates chance such that (a) both choices are equally likely to be selected and (b) RTs for such a choice would be slow. When the subjective value difference between two choices is high, (a) drift rate is high and (b) a dominant selection preference for the higher-value choice emerges along with (c) fast RTs. Moreover, when option A has a higher subjective value than option B, the subjective value difference (*A - B*) will be positive and the drift rate will be positive, thus option A will be preferred over option B. If option B has a higher subjective value, the subjective value difference will be negative and the drift rate will be negative, thus option B will be preferred over option A.

Using the MMT framework, the subjective value of entertainment media should be determined by the affective attributes of the media content and each individual's mood and content preferences, which function as weights. For a person who is in a negative mood, positive content will have a higher potential gain, which will increase the likelihood of selecting positive content. Whereas, for a person who is in a positive mood, the potential gain from positive content might not be as strong as the person in a negative mood. Hence, following Roberts and Hutcherson (2019), we propose that affective attributes of media content contribute to the expected subjective value of a choice in a weighted linear way:

$$\mathrm{SV}_{\mathrm{choice}} = \sum_a W_a * \mathrm{Attribute}_{\mathrm{a}} \qquad \text{Equation 1}$$

In Equation 1, *SV* represents the expected subjective value of a choice (media content), *Attribute* represents an affective attribute of the media content, and *W* represents the attribute weight. Consistent with MMT, we focus on valence and arousal as affective attributes of media content, and propose that:

$$\mathrm{SV}_{\mathrm{choice}} = \mathrm{W}_{\mathrm{arousal}} * \mathrm{Arousal} + \mathrm{W}_{\mathrm{valence}} * \mathrm{Valence} \qquad \text{Equation 2}$$

To test this multi-attribute value-based drift diffusion model (Busemeyer et al., 2019), we need a series of two-choice decision tasks that carefully differentiate the effects from either one of the affective attributes (i.e., valence, arousal) or both. We expect that drift rate (v) is a function of the value difference between two choices:

$$v = \mathrm{SV}_{\mathrm{choiceA}} - \mathrm{SV}_{\mathrm{choiceB}} \qquad \text{Equation 3}$$

Accordingly, we developed a choice set that included four categories of movie stimuli (arousal high/low *x* valence positive/negative). Combining the movie stimuli from these four categories gives 10 possible decision types, which are reducible to five mutually exclusive and completely exhaustive types of decision tasks (Supplementary Section 1). We derive falsifiable hypotheses from MMT and test them by comparing the DDM parameters estimated from these five decision tasks. In the following sections, we report the rationale, hypotheses, and results for three studies that use the DDM to test core predictions derived from MMT.

Open science practices

Following calls for open science practices in communication (Dienlin et al., 2021; Lewis, 2020), our hypotheses were preregistered (https://osf.io/tb3ca/). The code for stimulus generation, the stimuli themselves, the PsychoJS code required to run each experiment, the raw data, and the Python and R code for data analysis is posted on GitHub (https://github.com/cogcommscience-lab/movie_selection).

Study one

A core prediction of MMT is that people have a preference for positively valenced media content. Therefore, we expect a positively signed drift rate for valence such that: (H1a) The group-level drift rate in a decision task with only a valence difference (1V0A) is positive (above 0), and (H1b) the group-level drift rate in a decision task with only a valence difference (1V0A) is higher than the decision task with no valence and no arousal difference (0V0A). Moreover, based on MMT, we expect that drift rate, determined by movie valence, is also shaped by people's current mood valence, meaning that individuals in a negatively valenced mood will have a higher drift rate (preference) toward positively valenced movie options. Therefore, (H2) the individual-level drift rate in a decision task with only a valence difference (1V0A) is negatively correlated with people's prevailing mood valence.

The excitatory homeostasis prediction of MMT states that media preferences are determined by prevailing arousal, meaning that under-stimulated individuals would have a positively signed drift rate (preference) toward a high-arousal movie option, while over-stimulated individuals would have a negatively signed drift rate (avoidance) toward a high-arousal movie option. Accordingly, we expect that (H3) the individual-level drift rate in a decision task with only an arousal difference (0V1A) is negatively correlated with people's prevailing excitatory state.

Additionally, we ask exploratory questions to determine if people have a basic preferential tendency toward high or low-arousal movies: (RQ1a) Is the group-level drift rate in a decision task with only an arousal difference (0V1A) negative (preference for low-arousal), positive (preference for high arousal), or not distinct from 0 (no clear preference) and (RQ1b) is the group-level drift rate in a decision task with only an arousal difference (0V1A) negative (preference for low-arousal), positive (preference for high arousal), or not distinct from the decision task with no valence and no arousal difference (0V0A)?

Moreover, based on the proposed additive linear model (Equation 2) combining both arousal and valence attributes as integral parts of subjective value in determining movie choice, we expect an additive effect of arousal and valence on drift rate in decision tasks that differ on both arousal and valence. This hypothesis is based on the logic described above demonstrating that, as the subjective value difference (Equation 3) between two choices increases, drift rates become faster (high-drift rate). Therefore, (H4a) the decision task with both valence and arousal differences in the same direction (1V1A) will have a higher group-level drift rate compared with drift rate in decision tasks involving only either valence or arousal (1V0A or 0V1A).

Similarly, when valence and arousal are integrated in an opposite direction (similar to the value of valence minus the value of arousal), the integrated value becomes smaller than the value of valence or arousal alone. Therefore, (H4b) the decision task with both valence and arousal differences in the opposite direction (1V-1A) will have a lower group-level drift rate compared with drift rate in decision tasks involving only either valence or arousal (1V0A or 0V1A).

Method

Stimulus generation

Single-sentence movie summaries were generated using natural-language processing techniques to shorten paragraph-length plot descriptions from 42,306 films (Bamman et al., 2013). A dictionary-based approach was then used to label each movie summary on two dimensions, arousal and valence (Bradley & Lang 1999; Warriner et al. 2013). Following best-practices for using dictionary-based approaches (Song et al., 2020), the arousal and valence labels were then cross validated using self-assessment manikin (SAM; Bradley & Lang, 1994) ratings from human annotators ($n = 164$). This resulted in a final dataset of 56 stimuli that systematically varied on arousal (high/low) and valence (positive/negative; Supplementary Section 1).

Decision-making task

This experiment was conducted on https://pavlovia.org/. At the beginning of the experiment, participants self-reported their prevailing mood state using the SAM (Bradley & Lang, 1994), which captures feelings of valence and arousal. Then participants rated eight movie summaries using the SAM (Figure 1B) as a training block in order to familiarize participants with each of the summaries. Next, in a testing block, participants were presented with a series of two-choice decision tasks consisting of the movie summaries shown in the previous training block (20 trials, four trials for each decision type). The decision trials were randomly and independently generated for each participant. Participants chose their preferred option as quickly as possible. Choice and RT were recorded (Supplementary Section 2). This training-then-testing procedure was repeated for a total of seven training and testing blocks. Lastly, participants provided demographic and media preference information.

Analysis

To test our hypothesis and questions, we applied a hierarchical Bayesian drift-diffusion model (HDDM; Gong & Huskey, in press; Wiecki et al., 2013) to the choice and RT data (Supplementary Sections 3 and 4). To aid in interpretation, we fixed the upper boundary to be the choice with higher arousal or valence, and lower boundary to be the choice with lower arousal or valence (as determined in the stimulus generation pretest). This means that a positively signed drift rate indicates a preference for high arousal or positively valenced movie choices, whereas a negatively signed drift rate indicates a preference for low arousal or negatively valenced movie choices. HDDM generates a posterior probability distribution for both group- and individual-level drift rate parameters for the decision process. We applied three common procedures to deal with contamination RTs (Supplementary Section 5). Inferential testing was conducted on the posterior probability distributions using Bayesian logic.

Sample

Participants were $n = 140$ undergraduates from the University of California Davis. Sample characteristics are reported in Supplementary Section 6 and preregistered exclusion criteria are discussed in Supplementary Section 7. This sample size was based on a power analysis of a regression model ($p < .05$; 90% power; $d = 0.1$) conducted using GPower (Faul et al., 2007). This estimated sample ($n = 140$) was then used in a subsequent and more precise power analysis which simulated 100 datasets, each with 140 subjects, with varying drift rates. A HDDM was estimated for each dataset. Results indicate that a sample size of $n = 140$ provides very high power (94% power; $d = 0.1$). Complete code for conducting the simulations and calculating power can be found on the project's GitHub repository.

Results

Manipulation checks show that our movie summaries systematically varied along arousal and valence dimensions as expected (Supplementary Section 8). We report the mean and 95% credible interval for each posterior probability distribution. Bayesian inference testing is done by comparing one posterior probability distribution against another (as specified by our hypotheses)—resulting in a distribution of differences—which is compared against zero (Kruschke, 2013). For hypotheses where a comparison between posterior probability distributions is not specified, we test a single posterior probability distribution against zero. The percentage of posterior greater than 0 and less than 0 is reported. For example, 100.0% < 0 < 0.0% indicates that 100.0% of posteriors are smaller than 0 and 0.0% of posteriors are larger than 0. Results where 97.5% of the distribution is > 0 (or < 0) are considered credible.[3]

Valence hypotheses

For tasks that differed only in the valence of the stimuli (1V0A), we expected a positively signed drift rate that is credibly different from zero (H1a) and higher drift rate compared to tasks with no valence or arousal difference (0V0A; H1b). These hypotheses were not supported (Figure 2A, left). Instead, the drift rate for higher valence movies ($M = -0.162$, 95% CI [−0.212, −0.111]) is negative, credibly different from zero (100.0% < 0 < 0.0%), and credibly lower (100.0% < 0 < 0.0%) than the 0V0A drift rate ($M = -0.004$, 95% CI [−0.053, 0.045]). This means that participants have a preference for negatively valenced movies. The 0V0A drift rate was centered about zero, which indicates that participants' responses to these tasks were essentially at chance; that is, participants were equally likely to choose either option during 0V0A tasks in which the two options had no difference in valence and arousal (as would be expected within a value-based decision-making framework).

We also expected that, for tasks differing only in valence (1V0A), we would see a negative correlation between prevailing valence mood state and drift rate (H2). We found that the prevailing valence mood state has no credible relationship with drift rate ($M = 0.010$, 95% CI [−0.041, 0.060], 35.7% < 0 < 64.3%). Thus, H2 did not have credible evidence (Figure 2A, right).

Arousal hypotheses

H3 specified that the drift rate in tasks with only arousal differences (0V1A) will be negatively correlated with people's prevailing mood arousal. There was no credible evidence for this hypothesis (Figure 2A, right; $M = 0.004$, 95% CI [−0.023, 0.031], 39.2% < 0 < 60.8%). RQ1a asked if participants had a preference for high-arousal movies in tasks with only arousal differences (0V1A). Our results indicate that the drift rate in tasks with only arousal differences (0V1A; $M = 0.014$, 95% CI [−0.034, 0.064]) is not credibly different from zero (28.9% < 0 < 71.1%). Finally, RQ1b asked if participants had a stronger preference for tasks that differed in arousal only (0V1A) relative to tasks that did not differ on either attribute (0V0A). We found no credible difference (30.3% < 0 < 69.7%) between the drift rates. Together, these results show that participants have no clear preference for arousal attributes of movies in the decision task.

Multi-attribute (valence and arousal) hypotheses

H4a and H4b specified an additive influence of valence and arousal on drift rates. Thus, we compared drift rate of tasks differing in both arousal and valence (1V1A & 1V-1A) to drift rate of tasks differing in only arousal or valence (0V1A, 1V0A). Our results showed that the posterior probability distributions for drift rates are signed differently (0V1A is positive; 1V0A, 1V1A & 1V-1A are negative). Therefore, we tested H4a and H4b by evaluating the magnitude difference between the drift rates by converting the estimated drift rates of 1V0A, 1V1A, and 1V-1A to be positive before the comparison. For H4a, the drift rate magnitude in tasks with both valence and arousal differences (1V1A) is credibly higher than drift rate magnitude in task with only arousal difference (0V1A; 0.0% < 0 < 100.0%), but not credibly higher than in tasks with only valence differences (1V0A; 22.8% < 0 < 77.2%). Similarly, for H4b, the results indicate that drift rate magnitude in tasks with both valence and arousal differences in the opposite direction (1V-1A) is credibly higher than drift rate magnitude with only arousal differences (0V1A; 0.0% < 0 < 100.0%), but not credibly higher than in tasks with only valence differences (1V0A; 42.6% < 0 < 57.4%). Thus, both H4a and H4b were partially credible.

Finally, we note that the value of drift rate posterior distribution is 1V-1A < 1V0A < 1V1A < 0V0A < 0V1A (Figure 2A, left). This order partially supports our hypothesis that the effect of valence and arousal on drift rates is additive, although primarily negatively signed.

Exploratory analyses

These findings provide no evidence for our hypotheses drawn from MMT. In fact, several results directly, and credibly, contradict core MMT valence and arousal predictions. Were we using solely experimental data, we would at this point be at a loss. However, using a computational model allows us to probe these contradictions. First, we broadened our analytical approach to a general linear model framework where we can estimate DDM model parameters by treating attributes (arousal, valence) as factors in a regression model. Second, the DDM has three additional parameters in addition to drift rate: non-decision time, decision boundary, and decision bias. Our exploratory analyses investigated these parameters in a full DDM model.

In order to estimate the effects of valence and arousal on the full DDM, we fit a regression model on the decision tasks (excluding the 1V-1A decision task) with valence and arousal as factors in a 2 (valence high/low) x 2 (arousal positive/negative) design. Factors were dummy-coded based on the stimulus generation pretest (low/negative = 0, high/positive = 1). Importantly, DDM is always comparing choices (i.e., choiceA vs. choiceB). Therefore, these factors were then subtracted from eachother such that 0 = no difference between choices and 1 = difference between choices). Accordingly, the parameter estimate represents the magnitude and directionality of the higher factor-level (i.e., difference between choices) relative to the lower factor-level (i.e., no difference between choices). We then tested whether the estimated posterior distributions for the main effects (for both valence and arousal) and the interaction effect were different from zero for each

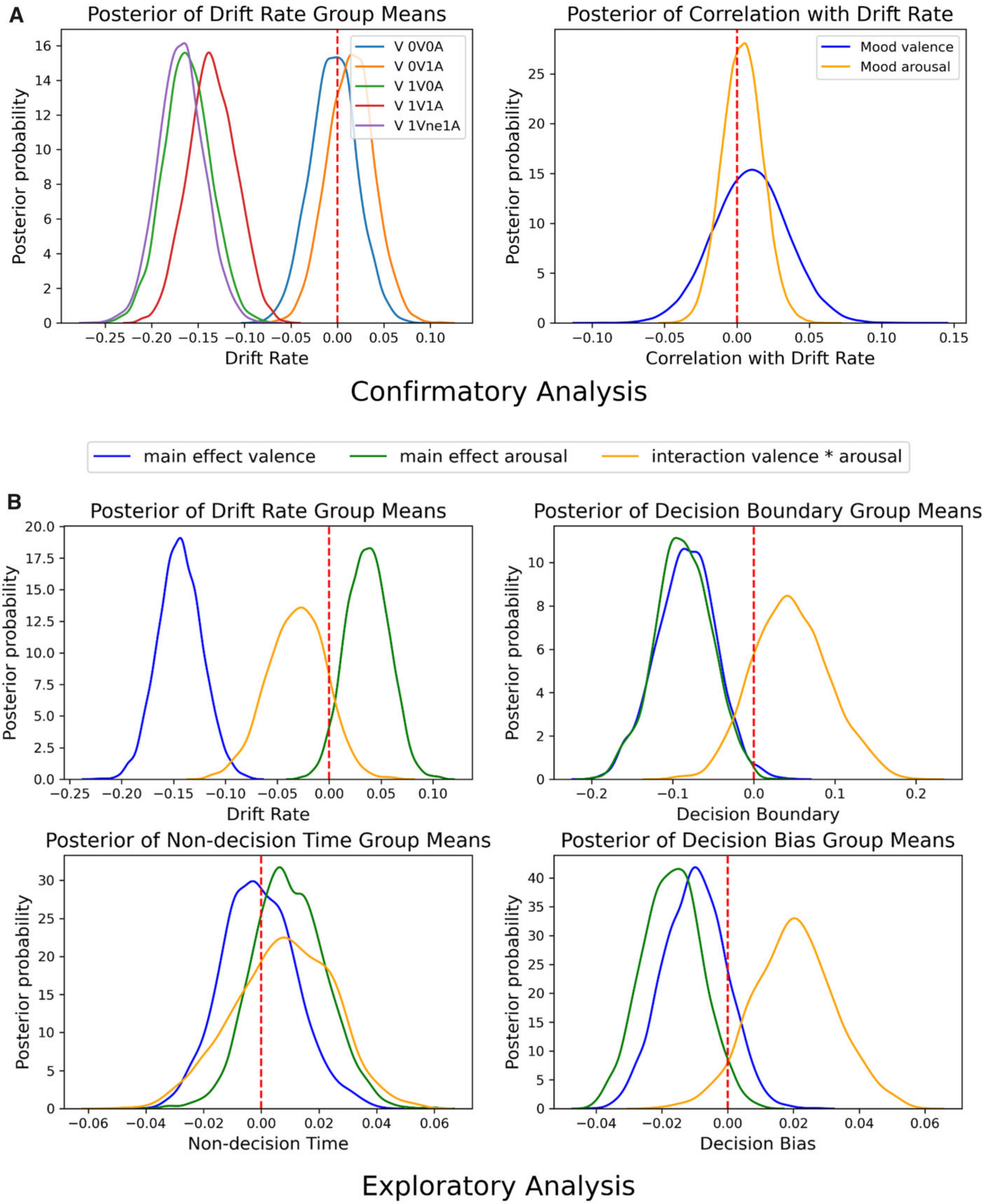

Figure 2 (**A**) Confirmatory analysis, study 1. The left plot shows the posterior probability distributions for drift rates in decision tasks with distinct valence/arousal differences. The right plot shows the posterior distributions for the effects of mood valence and mood arousal on drift rate. (**B**) Exploratory analysis, study 1. Posterior probability distribution of the effects of valence, arousal and their interaction on drift rate (upper left), decision boundary (upper right), non-decision time (bottom left) and decision bias (bottom right) in the full DDM model.

DDM model parameter (drift rate, decision boundary, decision bias, and non-decision time).

The results (Figure 2B) suggest that (a) valence has a credible negative main effect on drift rate (M = -0.144, 95% CI [−0.183, −0.102], 100.0% < 0 < 0.0%) and decision boundary (M = −0.084, 95% CI [−0.158, −0.015], 98.8% < 0 < 1.2%), but no credible effect on non-decision time (M = −0.001, 95% CI [−0.025, 0.026], 53.2% < 0 < 46.8%) or decision bias (M = −0.010, 95% CI [−0.028, 0.008], 85.4% < 0 < 14.6%), (b) arousal has a credible negative main effect on decision boundary (M = −0.087, 95% CI [−0.159, −0.020], 99.8% < 0 < 0.2%), but no credible effect on drift rate (M = 0.037, *95% CI* [−0.002, 0.076], 3.4% < 0 < 96.6%), non-decision time (M = 0.010, 95% CI [−0.014, 0.035], 21.7% < 0 < 78.3%), or decision bias (M = −0.017, 95% CI [−0.034, 0.000], 96.6% < 0 < 3.4%), (c) the interaction between arousal and valence does not have credible effect on drift rate (M = −0.031, 95% CI [−0.088, 0.022], 87.2% < 0 < 12.8%), decision boundary (M = 0.046, *95% CI* [−0.042, 0.142], 16.5% < 0 < 83.5%), decision bias (M = 0.020, 95% CI [−0.005, 0.045], 5.2% < 0 < 94.8%) or non-decision time (M = 0.008, 95% CI [−0.027, 0.039], 31.7.0% < 0 < 68.3%). In sum, valence has a credible main effect on drift rate, and both arousal and valence have credible main effects on boundary.

Discussion

Our preregistered results for study one largely do not support our main hypotheses. First, we failed to find evidence for the MMT hypothesis that people have a preference toward positively valenced movies. Instead, we found credible evidence that people prefer negatively valenced movies. This finding is also confirmed in our exploratory analysis. Second, we did not detect a preference for arousal. Third, we found a credible drift rate difference when valence and arousal effects are additive (1V1A & 1V-1A) compared to tasks with only arousal differences (0V1A), but not to tasks with only valence differences (1V0A). We also found the order of the drift rate posterior is largely consistent with the additive model. Finally, we failed to find the effect of people's prevailing mood on people's preference for movies with different valence and arousal.

In sum, these findings, particularly related to valence, challenge hypotheses drawn from MMT. However, MMT hypotheses are concerned with the effect of existing mood on media selection, and unlike many MMT studies, we did not include a mood induction in study one. As such, we conducted a follow-up study that experimentally manipulated mood state.

Study two

Using the MMT logic explicated above, we expected that induced mood (valence and arousal) would interact with people's preference for the corresponding affective attributes (valence and arousal) of movie choices when people are evaluating the subjective value of movies. We hypothesized an interaction effect for mood valence such that: (H1a) individuals in the negative-mood valence condition will have a positively signed drift rate toward positive-valence movies (upper boundary) and (H1b) individuals in the positive-mood valence condition will have a negatively signed drift rate toward negative-valence movies (lower boundary).

Similarly, we also hypothesized an interaction effect for arousal such that: (H2a) participants in the low-mood arousal condition will have a positively signed drift rate towards high-arousal movies (upper boundary) and (H2b) participants in the high-mood arousal condition will have a negatively signed drift rate towards low-arousal movies (lower boundary). We also asked if: (RQ1) The MovieValence × MoodValence or MovieArousal × MoodArousal interaction more strongly influences drift rate.

Finally, in study one, for arousal and valence, we saw negatively signed parameter estimates for decision boundary. What does this mean? Decision boundary is often interpreted as a measure of response caution (Ratcliff et al., 2016; Roberts & Hutcherson, 2019). Wider decision boundaries are associated with lower (slower) drift rates, more cautious decisions, and in instances where there is an objectively correct decision, decreased error rates. By comparison, narrower decision boundaries are associated with higher (faster) drift rates, less cautious decisions, and increased error rates. That the main effects for arousal and valence are credible and negatively signed tells us that, when the subjective value difference between two choices is high, people become faster and less cautious in their decision making. To our knowledge, there is no theory of media selection that accounts for this finding.

Therefore, in study two, we sought to replicate the decision boundary effects observed in study one, testing if high subjective value differences between media choices could make people select specific movies faster. Specifically, we expected that both (H3a) movie valence and (H3b) movie arousal will have a negative main effect on decision boundary. We also asked if participants' mood states influences decision boundary. Does (RQ2) mood valence and (RQ3) the interaction between mood valence and movie valence have a credible effect on decision boundary? Similarly, we will also test if: (RQ4) mood arousal and (RQ5) the interaction between MoodArousal and MovieArousal have a credible effect on decision boundary.

Method

For study two, the decision tasks remained identical to study one, however, in addition to the decision tasks, we added a mood induction procedure (from Kuijsters et al., 2016; see Supplementary Section 9 for description) after presenting participants with the movie summaries in the training phase, but before participants made preferential choices in the decision tasks. Participants were randomly assigned to one of four mood induction groups: positive valence high arousal, positive valence low arousal, negative valence high arousal, and negative valence low arousal. Within each group, participants were instructed to view randomized and counter-balanced stimuli presentations of images for the corresponding mood induction. The stimulus manipulation (Supplementary Section 8) as well as the mood induction were successful (Supplementary Section 10). For each group, the mood induction procedure was repeated before each experimental block. In other words, the procedure for each experimental block (n = 7) was as follows: movie summary text presentation (training) → mood induction → SAM mood rating (induction check) → decision tasks (testing; Figure 1B). Thus, the experiment was a 2 (mood induction arousal high/low) x 2 (mood induction valence positive/negative) x 2 (movie summary arousal high/low) x 2 (movie summary valence positive/negative) factorial design.

Analysis

We constructed a mixed model to estimate parameters in the decision task as follows:

$$v, \mathrm{a}, T, Z \ = \beta_{0\ |\ subject} \ + \ \beta_1 MoodValence \ + \ \beta_2 MovieValence \ + \beta_3 MoodValence * MovieValence + \ \beta_4 MoodArousal \ + \beta_5 MovieArousal \ + \beta_6 MoodArousal * MovieArousal + \varepsilon$$

Equation 4

Equation 4 estimates drift rate (v), decision boundary (a), non-decision time (T), and bias (Z). The terms encode main (MovieValence, MoodValence, MovieArousal, MovieValence) and interaction (MoodValence * MovieValence and MoodArousal * MovieArousal) effects. Preregistered model comparisons are reported in Supplementary Section 11.

To test the hypotheses and research questions, the estimated posterior distributions (v, a, T, and Z) for each decision type and each experimental condition were analyzed by using the *HDDMRegressor* function to fit a mixed model (with movie arousal and movie valence as within-subjects variables and mood valence and mood arousal as between-subjects variables). In this model, we specified random intercepts for subjects and fixed effects for the regressors. As in study one, each factor was dummy coded (low/negative = 0, high/positive = 1) and differences (0 = no difference between choices, 1 = difference between choices) were calculated. Therefore, the results reported for study two can be interpreted in the same way as study one.

Sample

Study two was also conducted on https://pavlovia.org/ and participants were undergraduate students. In total, $n = 127$ participants were sampled from the University of California, Davis (see Supplementary Section 6 for participant characteristics and Supplementary Section 12 for exclusion criteria). Power simulations show that the probability that a HDDM model can detect an effect asymptotes when participants per condition reaches $n > 25$ (Wiecki et al., 2013).

Results

Results are reported and inference testing is conducted consistent with study one.

Drift-rate hypotheses

We hypothesized an interaction effect such that people will have a positive drift rate toward positively valenced movies in the negatively valenced mood condition (H1a), and will have a negative drift rate toward negatively valenced movies in the positively valenced mood condition (H1b). Drift rates toward movie valence were negative in both the negatively valenced mood condition ($M = -0.124$, 95% CI [−0.168, −0.081], 100.0% < 0 < 0.0%) and in the positively valenced mood condition ($M = -0.058$, 95% CI [−0.103, −0.014], 99.6% < 0 < 0.4%). Thus, H1b is supported, but H1a is not, as people show a preference for negatively valenced movies regardless of their mood valence. Additionally, we found that people in a negative mood state had a lower drift rate than people in a positive mood state (98.3% < 0 < 1.7%).

We can further explore this result by examining the main and interaction effects for movie and mood valence (for cell means, see Supplementary Section 13). The results of the regression model (Figure 3A) show that movie valence has a negative main effect on drift rate ($M = -0.129$, 95% CI [−0.172, −0.086], 100.0% < 0 < 0.0%), and the interaction between mood valence and movie valence is credible and positive ($M = 0.072$, 95% CI [0.012, 0.134], 0.8% < 0 < 99.2%). This interaction means that, contrary to what we expected, participants in a negative mood have a stronger preference for negatively valenced movies (Figure 3B).

Similarly, we expected (H2a) that people will have a *positive* drift rate toward high-arousal movies in low mood arousal condition, and (H2b) will have a *negative* drift rate toward low-arousal movies in the high-mood arousal condition. We show (Figure 3A) that participants in the low-mood arousal condition had a credible and *positive* drift rate toward high-arousal movies ($M = 0.048$, *95% CI* [0.005, 0.090], 1.4% < 0 < 98.6%). Participants in high-mood arousal condition had also a credible *positive* drift rate toward high-arousal movies ($M = 0.057$, 95% CI [0.012, 0.101], 0.7% < 0 < 99.3%). There is no credible difference between the effects at different levels of mood arousal (61.4% < 0 < 38.6%).

We also examined the hypotheses by investigating the main and interaction effects for movie and mood arousal (for cell means, see Supplementary Section 13). Movie arousal has a positive main effect on drift rate ($M = 0.046$, 95% CI [0.006, 0.088], 1.4% < 0 < 98.6%). However, the interaction between mood arousal and movie arousal was not credible ($M = 0.011$, 95% CI [−0.048, 0.071], 35.8% < 0 < 64.2%). Instead, people prefer high-arousal movies regardless of their mood arousal, supporting H2a but not H2b (Figure 3C).

RQ1 compared the effect size of the interaction between mood valence and movie valence with the effect size of the interaction between mood arousal and movie arousal. The difference between the two interaction effects was not credible (8.1% < 0 < 91.9%).

Decision boundary hypotheses

H3a and H3b specified that movie valence and movie arousal would have a negative main effect on decision boundary. Results (Figure 3A) show that only movie valence has a negative effect on decision boundary ($M = -0.170$, 95% CI [−0.242, −0.103], 100.0% < 0 < 0.0%). Movie arousal did not have a credible main effect on decision boundary ($M = -0.052$, 95% CI [−0.132, 0.030], 90.0% < 0 < 10.0%). Thus, H3a is supported, but H3b is not.

Finally, we asked if mood valence (RQ2), the interaction between mood valence and movie valence (RQ3), mood arousal (RQ4), and the interaction between mood arousal and movie arousal (RQ5) had credible effects on decision boundary. Results show that mood valence ($M = -0.027$, 95% CI [−0.239, 0.177], 60.4% < 0 < 39.6%), mood arousal ($M = -0.117$, 95% CI [−0.355, 0.105], 85.6% < 0 < 14.4%), the interaction between mood valence and movie valence ($M = 0.064$, 95% CI [−0.033, 0.165], 10.4% < 0 < 89.6%), and the interaction between mood arousal and movie arousal ($M = 0.003$, 95% CI [−0.106, 0.109], 47.3% < 0 < 52.7%) do not credibly influence decision boundary.

Exploratory analyses

Mood arousal has a credible negative effect on non-decision time ($M =$ -0.264, 95% CI [−0.422, −0.119], 100.0% < 0 < 0.0%). This means that participants in higher arousal mood take less time (∼0.26 s) on reading the decision task options and/or executing the decision (e.g., button press). Other effects for non-decision time and decision-bias were not credible.

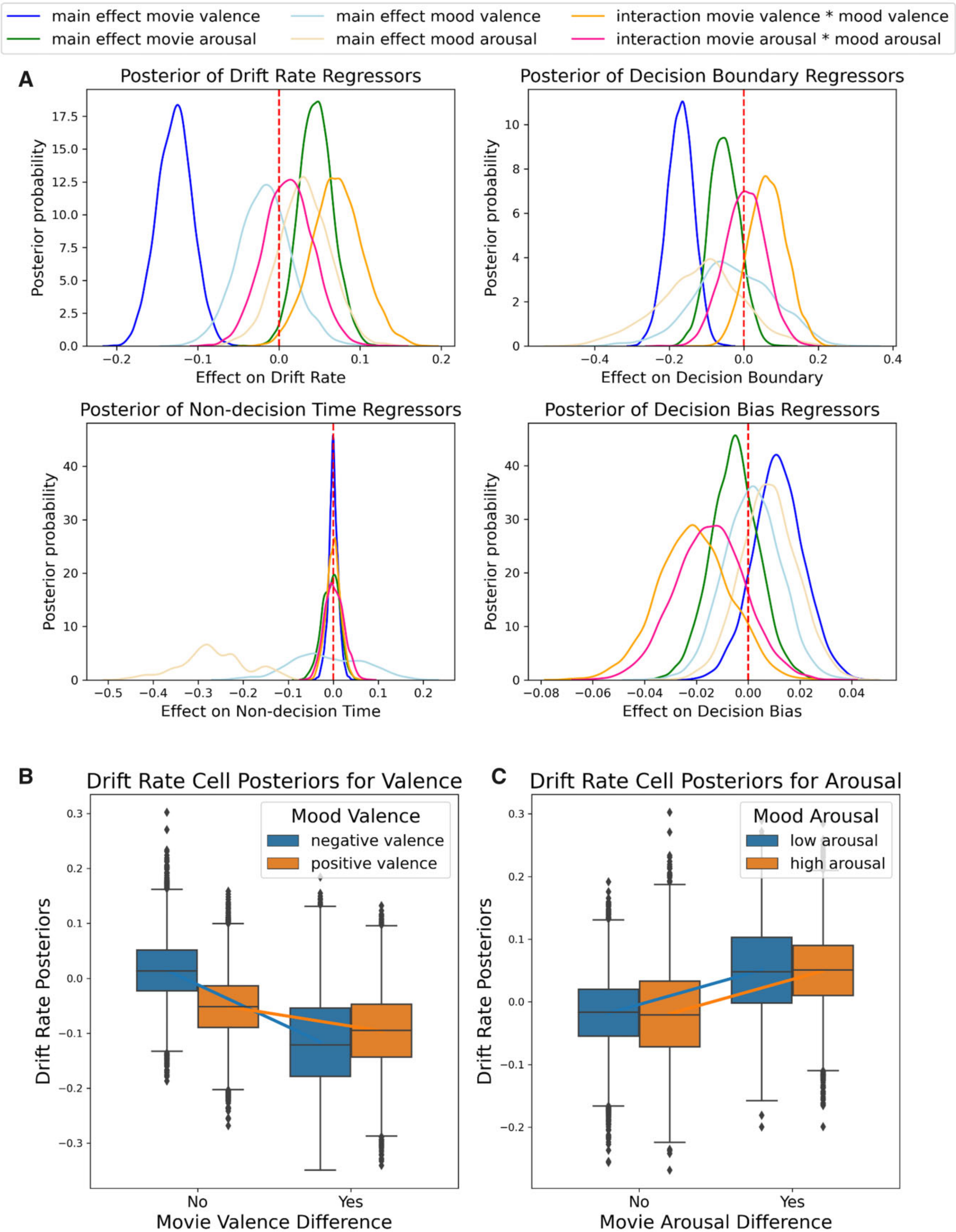

Figure 3 (**A**) Confirmatory analysis, study 2. Posterior probability distributions for the effects of movie valence/arousal, mood valence/arousal, and their interactions on drift rate (upper left), decision boundary (upper right), decision bias (bottom left), and non-decision time (bottom right). (**B**) Interaction effect between mood valence and movie valence. (**C**) Interaction effect between mood arousal and movie arousal.

Discussion

In study two, we tested hypotheses drawn from MMT by inducing specific mood states prior to a media decision-making task. We successfully induced positive or negative mood states of high or low arousal, and fit a HDDM regression model on people's RT and choice data.

Study two replicated study one in that people showed a preference toward negatively valenced content. Moreover, mood valence and movie valence had a credible interaction effect on drift rate. Contrary to the valence hypothesis of MMT, participants in our study showed a stronger preference toward negatively valenced movies when in a negatively valenced mood. On the other hand, movie arousal had a positive effect on drift rate, meaning participants showed a preference toward high-arousal movies when they are in a low-arousal state—which supports MMT's excitatory potential prediction. Contrary to MMT, participants also showed a trend towards high-arousal movies even when they were in a high-arousal state.

Lastly, we replicated the effect of movie valence on the decision boundary from study one, finding that higher subjective value differences between choices makes people less cautious in their decisions.

Study three

Studies one and two were conducted using a college student sample during the Covid-19 pandemic (2020 and 2021, respectively). In order to increase the generalizability of our findings, we conducted a third study that directly replicated study two in a more representative sample of American adults. Study three was conducted in April 2022, after the introduction and widespread availability of the Covid-19 vaccine (2021) and lifting of many Covid-19 related restrictions.

Method

Analysis

The hypotheses, experimental design, data cleaning, model, and data analysis procedure were identical to study two. The stimulus manipulation (Supplementary Section 8) and mood induction were successful (Supplementary Section 10).

Sample

$N = 301$ participants that were approximately representative of the United States population (in terms of age, gender, and ethnicity) were recruited from Prolific Academic (see Supplementary Section 6 for participant characteristics and Supplementary Section 14 for exclusion criteria). Participants were compensated \$7.92 for their time ($M = 59.324$ minutes, $S.D. = 24.602$). The task was hosted on https://pavlovia.org/.

Results

In study three, we expected that the previously specified HDDM regression model (Equation 4) would replicate study two's findings.

Drift-rate hypotheses

H1a specified that participants in the negative mood valence condition would have a positively signed drift rate whereas H1b specified that participants in the positive mood valence condition would have a negatively signed drift rate. Neither H1a ($M = -0.023$, 95% CI [−0.052, 0.006], $94.0\% < 0 < 6.0\%$) or H1b ($M = -0.008$, 95% CI [−0.037, 0.019], $72.1\% < 0 < 27.9\%$) were supported. As in study two, we also interrogated the main and interaction effects for movie and mood valence (for study three cell means, see Supplementary Section 15). The regression model (Figure 4A) shows that the negative main effect of movie valence on drift rate ($M = -0.024$, 95% CI [−0.052, 0.004], $95.1\% < 0 < 4.9\%$) is not credible. The mood valence and movie valence interaction are also not credible ($M = 0.015$, 95% CI [−0.025, 0.056], $24.2\% < 0 < 75.8\%$). In sum, H1a and H1b were not supported, and they did not replicate the results from study two.

H2a specified that participants in the low mood arousal condition will have a positively signed drift rate, whereas H2b specified that participants in the high mood arousal condition will have a negatively signed drift rate. Neither H2a ($M = -0.043$, 95% CI [−0.072, −0.014], $53.8\% < 0 < 46.2\%$) or H2b ($M = 0.009$, 95% CI [0.020, 0.039], $2.4\% < 0 < 97.6\%$) were supported. Examination of the main and interaction effects for mood and movie arousal (Figure 4A; cell means, Supplementary Section 15) showed that movie arousal ($M = -0.002$, 95% CI [−0.030, 0.025], $56.0\% < 0 < 44.0\%$) and the interaction between mood arousal and movie arousal ($M = 0.030$, 95% CI [−0.009, 0.072], $7.0\% < 0 < 93.0\%$) did not have a credible effect on drift rate. Here again, H2a and H2b were not supported and they did not replicate study two.

RQ1 compared the effect size of the interaction between mood valence and movie valence with the effect size of the interaction between mood arousal and movie arousal. As in study two, the difference between the two interaction effects was not credible ($M = 0.016$, 95% CI [−0.040, 0.076], $29.6\% < 0 < 70.4\%$).

Decision boundary hypotheses

It was expected that movie valence (H3a) and movie arousal (H3b) would have a negative main effect on decision boundary (Figure 4A). Movie valence showed a credible main effect ($M = -0.121$, 95% CI [−0.169, −0.071], $100.0\% < 0 < 0.0\%$), but not movie arousal ($M = 0.000$, 95% CI [−0.026, 0.027], $56.0\% < 0 < 44.0\%$). Thus, H3a was supported and replicated the result observed in study two. H3b was not supported in either study two or three.

Turning now to our research questions, we see that mood valence (RQ2; $M = 0.015$, 95% CI [−0.121, 0.099], $63.3\% < 0 < 36.7\%$), the interaction between mood valence and movie valence (RQ3; $M = 0.013$, 95% CI [−0.057, 0.081], $33.5\% < 0 < 66.5\%$), mood arousal (RQ4; $M = -0.017$, 95% CI [−0.147, 0.127], $66.2\% < 0 < 33.8\%$), and the interaction between mood arousal and movie arousal (RQ5; $M = 0.018$, 95% CI [−0.054, 0.083], $30.6\% < 0 < 69.4\%$) had non-credible effects on decision boundary. None of the decision boundary RQs were credible in study three. The same was true for study two.

Exploratory analysis

These confirmatory drift rate results do not replicate study two. However, we do see a credible replication of the negative main effect of movie valence on decision boundary. What explains these mixed replication results? One important distinction is that studies one and two were undergraduate students whereas participants in study three were approximately representative of the United States population and therefore

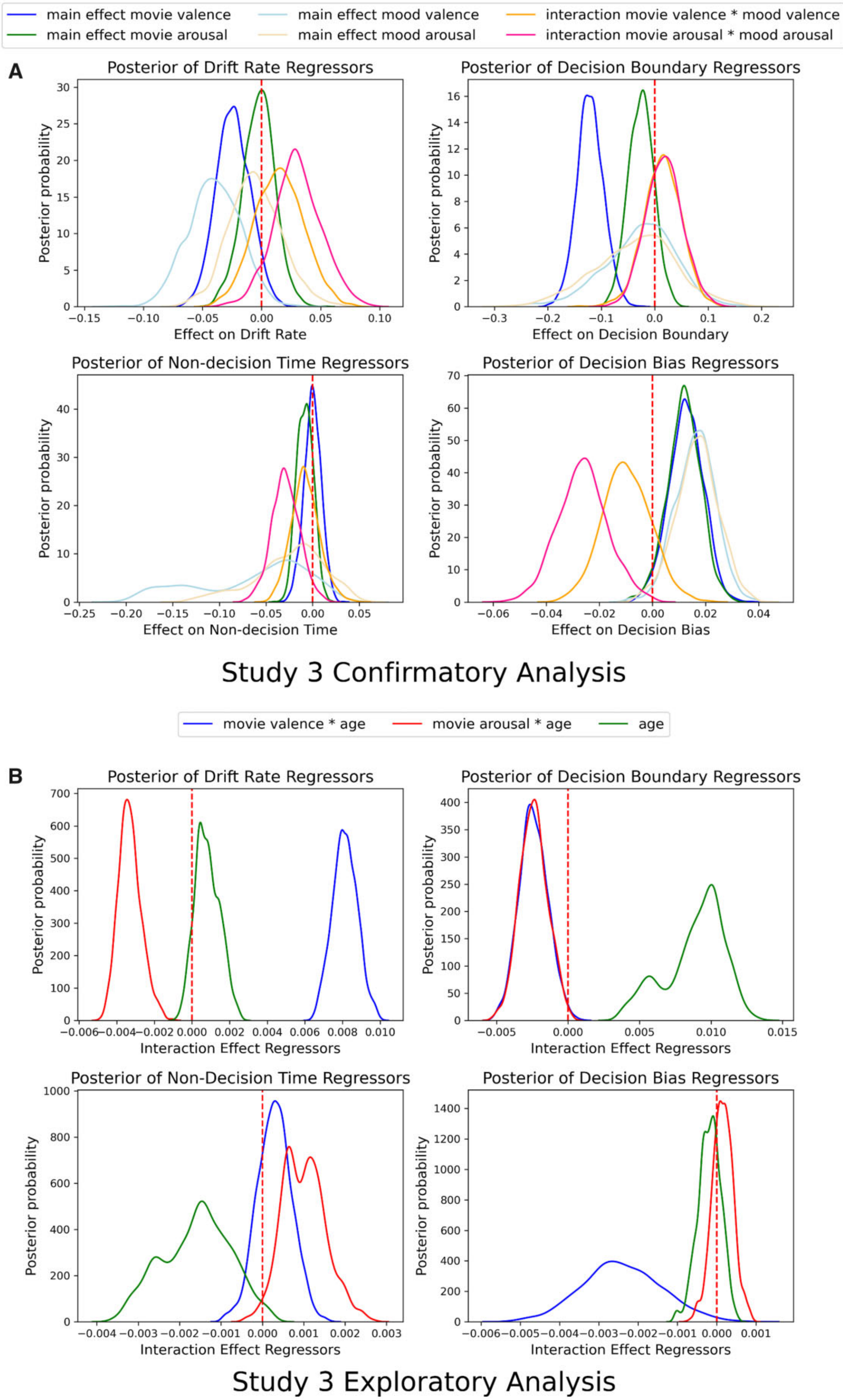

Figure 4 Study three posterior probability distributions for the effects of movie valence/arousal, mood valence/arousal, and their interactions on drift rate (upper left), decision boundary (upper right), decision bias (bottom left), and non-decision time (bottom right) for the (**A**) confirmatory, and (**B**) exploratory analysis.

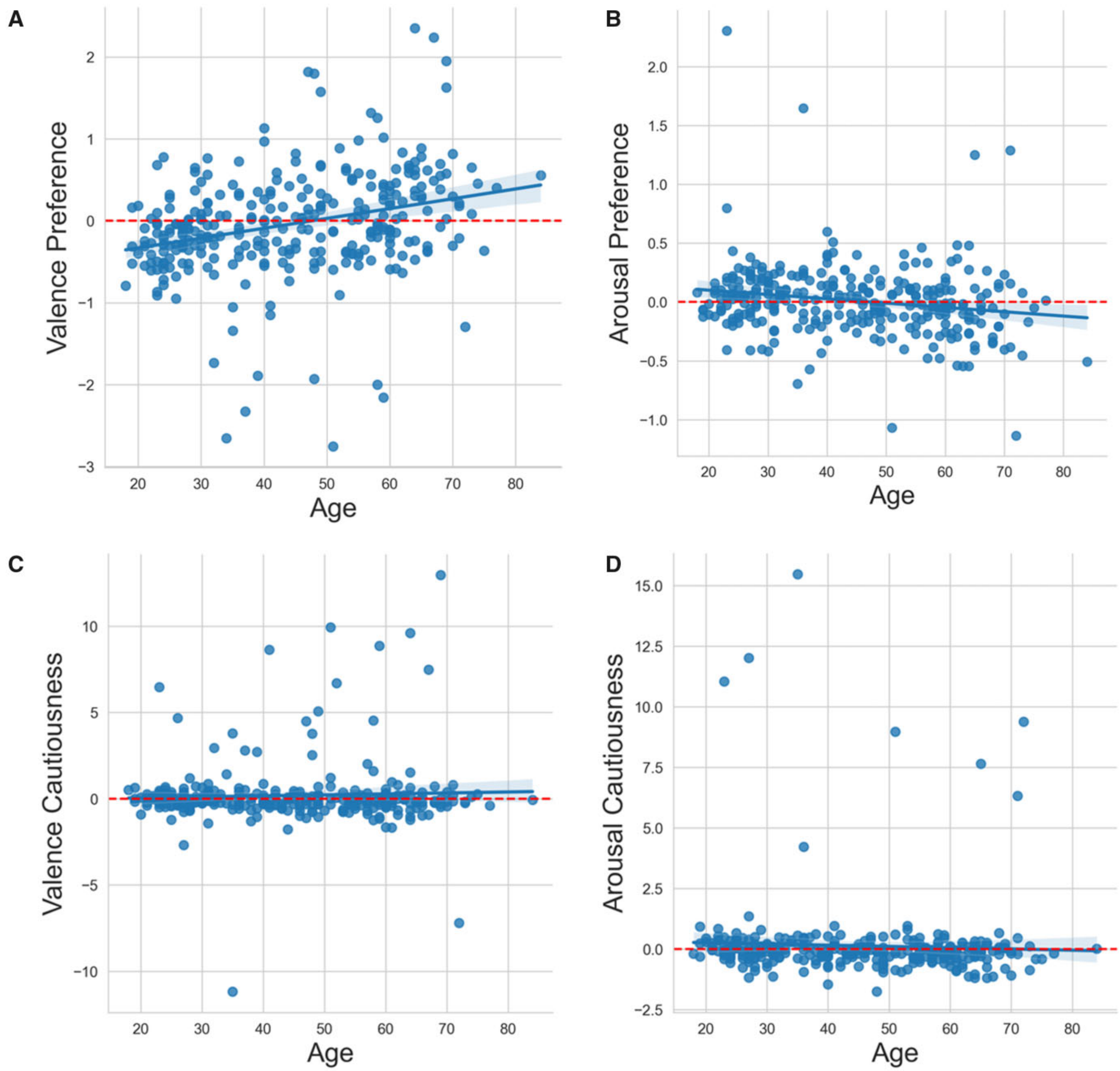

Figure 5 (**A**) Scatterplot showing the relationship between age and drift rate for movie valence. (**B**) Scatterplot showing the relationship between age and drift rate for movie arousal. (**C**) Scatterplot showing the relationship between age and decision boundary for movie valence. (**D**) Scatterplot showing the relationship between age and decision boundary for movie arousal.

comprised a wider range of ages. It could be that people's media preferences and mood management behaviors might differ by age. MMT does not specify age as a moderator. However, previous research has shown that media selection varies by age (Mares et al., 2008), and that older adults tend to prefer positively valenced media, especially for mood management (Mares et al., 2008; Shifriss et al., 2015).

Our results, particularly the negative main effect of movie valence on drift rate, are in the same direction as study two, and nearly meet our strict credibility threshold. If older adults do prefer positively valenced media whereas younger adults prefer negatively valenced media, then this preference could pull the negative main effect closer to zero, thereby washing out the main effect in the presence of a credible interaction effect. To test this possible explanation, we included the participant's age in the HDDM regression model as a moderator in the media selection process, as shown in Equation 5:

$$\begin{aligned} v, \mathrm{a}, T, Z = {} & \beta_{0 \mid subject} + \beta_1 MovieValence + \beta_2 MovieArousal \\ & + \beta_3 MoodValence + \beta_4 MoodArousal \\ & + \beta_5 Age + \beta_6 MoodValence * MovieValence \\ & + \beta_7 MoodArousal * MovieArousal \\ & + \beta_8 Age * MovieValence + \beta_9 Age \\ & * MovieArousal + \varepsilon \end{aligned}$$

Equation 5

When modeled this way, and consistent with study two, we see a credible negative main effect of movie valence

($M = -0.400$, 95% CI [-0.470, -0.333], 100.0% $< 0 <$ 0.0%) on drift rate. We also see a credible positive interaction effect between age and movie valence ($M = 0.008$, 95% CI [0.007, 0.009], 0.0% $< 0 <$ 100.0%) on drift rate (Figure 4B). This means that younger participants have a preference for negatively valenced movies whereas older participants have a preference for positively valenced movies (Figure 5A).

Also consistent with study two, movie arousal had a credible positive main effect ($M = 0.150$, 95% CI [0.083, 0.208], 0.0% $< 0 <$ 100.0%) on drift rate, Moreover, the interaction between age and movie arousal had a credible negative effect ($M = -0.003$, 95% CI [-0.004, -0.002], 100.0% $< 0 <$ 0.0%) on drift rate (Figure 4B). This shows that younger participants prefer high arousal movies and older participants prefer low-arousal movies (Figure 5B).

As in study two and the confirmatory model in study three, we still observed a credible negative main effect of movie valence (M $= -0.119$, 95% CI [-0.167, -0.068], 100.0% $< 0 <$ 0.0%) on decision boundary (Figure 4B). We also found a credible positive main effect of age ($M = 0.009$, 95% CI [0.004, 0.012], 0.0% $< 0 <$ 100.0%) and a negative interaction effect between age and both of movie valence ($M = -0.002$, 95% CI [-0.004, -0.000], 99.1% $< 0 <$ 0.9%) and movie arousal ($M = -0.002$, 95% CI [-0.004, -0.000], 99.4% $< 0 <$ 0.6%) on decision boundary. This shows that age influences people's media decision cautiousness such that older participants are generally more cautious in media selection, but will become less cautious when there is a difference in either valence (Figure 5C) or arousal (Figure 5D) among the media options.

Both movie arousal ($M = -0.046$, 95% CI [-0.094, -0.005], 98.8% $< 0 <$ 1.2%) and age ($M = -0.002$, 95% CI [-0.003, -0.000], 98.0% $< 0 <$ 2.0%) have a credible negative main effect on non-decision time. The main effect for age indicates that older participants take a shorter time to process and execute a media selection task compared to younger participants. The negative main effect for movie arousal means that participants take a shorter time to process and execute a media selection task when there is an arousal difference between the choices.

Finally, there is a credible positive main effect of both mood valence ($M = 0.015$, 95% CI [0.000, 0.029], 1.8% $< 0 <$ 98.2%) and mood arousal ($M = 0.016$, 95% CI [0.001, 0.031], 1.6% $< 0 <$ 98.4%) on decision bias (Figure 4B). This means that the experimental manipulation changes a participant's starting point to be biased toward positively valenced or high-arousal choices. There is also a credible negative interaction effect between mood arousal and movie arousal on decision bias ($M = -0.025$, 95% CI [-0.043, -0.006], 99.7% $< 0 <$ 0.3%), which means that a high-arousal mood biases people's decision starting point toward low-arousal movie choices.

Discussion

Our confirmatory model in study three failed to replicate the drift rate results observed in study two. However, the confirmatory model did replicate the decision boundary result observed in study two, namely that a valence difference between media choice options makes people less cautious in their decision making.

However, prior research has shown that people's use of media for mood management is moderated by age (Mares et al., 2008; Shifriss et al., 2015). Therefore, we constructed an exploratory model that included participant age. When doing so, we were able to reproduce the drift rate and decision boundary results observed in study two, this time in a more representative and heterogeneous sample of U.S. adults. People have a preference for negatively valenced and high-arousal media. When there is a valence difference between media choices, people's decision making becomes less cautious.

We also found that age has a critical moderating effect on media decision-making. Younger adults showed a strong preference for negatively valenced and high-arousal movies, while by comparison, older adults showed a preference for positively valenced and low-arousal movies. This distinct media preference among people of different ages is not a unique finding. Mares et al. (2008) found that younger adults were more inclined toward negative and arousing content, while older adults preferred emotional stability and positively valenced films. In news selection contexts, Bachleda et al. (2020) and Soroka et al. (2021) found that age is significantly associated with people's negativity bias such that younger adults have a stronger preference toward negative valenced news compared to older adults. Ossenfort & Isaacowitz (2018) found that older adults selected more positive-valenced games compared to young adults, and Livingstone and Isaacowitz (2015) found that older adults select positive media as a mood management strategy.

In line with this previous work, our results provide more evidence that people's media preferences change as they grow older. Our study is not well suited to explain why, as we did not examine change longitudinally. But it does suggest that age, which has been under-theorized in the literature, plays an important role in media selection, particularly when selection is framed as a decision-making process.

General discussion

In three studies, we applied a computational decision-making model (HDDM) to MMT, a central media selection theory. The results of all three experiments lead to a robust conclusion that people prefer negatively valenced over positively valenced movies, and high arousal over low-arousal movies, in decision-making tasks between two options. This preference holds, even after inducing different mood states (studies two and three). We also show that age moderates media content preferences (study three). Younger adults prefer negatively valenced and high-arousal media content, whereas these preferences are reversed among older adults. Finally, our results show that arousal and valence shape the subjective value of a media choice option, and that people's selection of media content is determined by the comparison of the subjective value differences between two media choice options, consistent with value-based decision theory.

Our project illustrates the utility of formal modeling for testing communication theory by applying a computational model of decision making to a well-known and established theory of media selection. Most communication theories and models are instantiated in what is known as a "verbal model" in which constructs central to a theory, and their relationships to each other, are verbally described, defined, and articulated (Shoemaker et al., 2004). Testing of these models is often conducted by collecting data and subjecting specific relationships between variables to NHST. The results of these tests are used to support, or fail to support, the verbally articulated relationships. MMT is a verbal theory. It has primarily been tested using experimental methods and NHST, receiving mixed support (Reinecke, 2016) .

As noted by Fisher and Hamilton (2021), one limitation of testing verbal theories is that there is room for individual experimenters to argue, for example, what exactly is specified by a theory, and how support for that hypothesis will be demonstrated or falsified. In this case, conceptual ambiguity on the part of scholars examining MMT hypotheses has led to mixed support for the theory (Knobloch-Westerwick, 2014). Computational or formal modeling, in contrast, translates verbal descriptions of variables into mathematical relationships between variables, which can be supported via mathematical proofs (in mathematical models), by using simulated data, or as in our study, experimental data to test the extent to which models hold under specific parameters (Fisher & Hamilton, 2021; Smaldino, 2020; van Rooij & Baggio, 2021). Thus, the risk of misinterpretation or inconsistent application of relationships is reduced, as are potential arguments about what constitutes disconfirming evidence.

An additional benefit of formal models is that when they fail, they fail "forwards," or productively. Even when formal models are tested and demonstrate evidence unsupportive of verbal theory, they do so in a way that allow for generative theory building. In the following section, we examine our results from the current studies in light of formal models. In doing so, we provide a generative path forward for media scholars interested in media selection.

Implications for MMT

Perhaps the most striking finding is the lack of confirmation for MMT's valence hypothesis. In three studies, we showed that people have a preference for negatively valenced content. In study one, we showed that people's prevailing mood state was unrelated to their media preferences. In study two we showed that a preference for negatively valenced media is amplified when people are experimentally induced into a negatively valenced mood. And in study three, we showed that age moderates media preference with younger adults preferring negatively valenced media whereas older adults prefer positively valenced media.

This preference for hedonically unpleasant media is not unique to our study. Indeed, research on why viewers would select tragic or sad films for entertainment (i.e., "the paradox of tragedy") has received substantial theoretical and research attention for three decades (Oliver, 1993). Explanations put forth for rationalizing why audiences select tragic films has included the implicit anticipation of meta-emotions form tragic film (Bartsch et al., 2008), self-determination theory-based psychological need satisfaction (Tamborini et al., 2010), the evolutionary benefits of fictional play (Steen & Owens, 2001), or the role of sad stories in evoking appreciation, nostalgia, or meaning (Oliver & Raney, 2011). We also note that this finding was moderated by age, in line with past research showing that younger viewers, in comparison to older, prefer negatively valenced media (Mares et al, 2008). Therefore, and in line with these studies, and from our own work here, we can confidently state that affect is not the sole or primary driver of media selection, as posited in the valence hypothesis of MMT.

We did find that arousal partially operates in line with MMT predictions. Individuals in a state of low arousal do select high-arousal films. However, we also saw a preference for high-arousal films among participants in a high-arousal state. This is similar to findings from Bryant and Zillmann (1984) who found no difference between stressed and relaxed participants in terms of the excitatory potential of selected television shows, as well as Strizhakova and Krcmar (2007), who found that nervous subjects preferred horror movies and sad subjects preferred crime dramas; both violations of MMT's excitatory homeostasis hypothesis.

One could argue that the preference for high-arousal films could be due to specific characteristics of our selection task or the sample we selected. Yet, additional analyses demonstrate that participants responded to each type of decision task in systematically similar ways (Supplementary Section 15). This means that our results were not driven by a small number of idiosyncratic choices in our study. It could be that the pandemic played a moderating role in media selection (Eden et al., 2020) that we did not account for (Holbert et al., 2022). However, it is worth noting that our mood induction in studies two and three were successful. Therefore, such a critique likely only applies to study one; although our successful mood induction nullifies this critique for studies two and three.

What does this mean for MMT and related theories of affect-based media choice? We would note that some core predictions from MMT were supported by our studies. Put differently, valence does influence decision-making, but does so by influencing the cautiousness of decisions. Studies two and three show that people make less cautious decisions when the subjective value difference between two choices is high. Therefore, to the scholar interested in studying media choice from a mood optimization perspective, we would suggest the following amendments to MMT and related theories.

First, media choice may be an insufficiently specified dependent variable for media selection studies. Decision cautiousness, in conjunction with selection, may more completely reflect the cognitive processes occurring during the selection period. Second, presentation order and comparative properties of the stimuli must be taken into account in future studies. Extensive theoretical accounts of the role of stimulus presentation or comparative effects are largely absent in media psychology studies, yet our finding suggests that presentation effects may be important to understand selective exposure broadly. When considering the practical implications, we may look towards Netflix or Hulu queues, which present several similarly-valanced films in a row. Based on our findings, this type of stimulus arrangement may push more cautious decision making, rather than if films with different attributes were presented together. However, the role of stimulus presentation is largely absent from selection theories. Third, media selection requires more extensive understanding and modeling of demographically-based moderators of choice such as age and context, as well as selected predictors of selection. Clearly, people make preferential decisions on entertainment movies not only based on the affective features, but also other features like empathy, psychological needs, genre, and emotion (Oliver, 1993; Tamborini et al., 2010; Oliver & Raney, 2011), as well as intrapersonal variables such as, individual goals and characteristics (Knobloch-Westerwick, 2014). To the extent to which these factors can be formally modeled, the potential for falsifying specific hypotheses increases. Fourth, we would suggest that media choice research move beyond the mood optimization hypothesis to examine other mechanisms driving media selection and more faithfully modeling the process. We turn to some of those models now.

Strengths and weakness of two-choice decision-making models for media research

As Smaldino (2017) notes, "Models are stupid, and we need more of them" (p. 311). When we use simple algorithmic representations of complex and dynamic relationships, there is room for disagreement about the manner in which variables have been selected and represented. Clearly, DDM comes with several practical constraints that potentially limit its applicability to test verbal theories. First, the parameterization procedure for transitioning theoretical constructs from verbal theories into latent variables requires accurate and solid measurement and manipulation of constructs. Second, DDM model fitting needs a relatively large sample of ubiquitous and homogeneous observations within experimental conditions for each participant with high consistency in experimental manipulation across trials. MMT itself suggests two additional predictions—semantic affinity and intervention potential—which we did not formalize in our work for the above two reasons; even if it may ultimately be possible to do so, in principle.

However, despite the narrow focus of our work, our study demonstrates how formalized "stupid" models can still elicit valuable theoretical insights. Our project represents the first ever formalization of MMT. To achieve this, we returned to first-principles by formalizing two core MMT predictions (the valence and excitatory homeostasis hypotheses). Future researchers might investigate alternative model parameterizations in an attempt to better formalize MMT, or investigate how previously undiscovered mechanisms (e.g., response caution) shape media selection. MMT assumes that affect-related media selection functions as an automatic and uncontrolled process (Zillmann, 1988). Given that this is a core assumption of MMT, it has not been rigorously tested. But decades of research show that automatic and uncontrolled processes are just one element that guides decision making. Decision making, including media selection, can also be governed by habit and intentional or goal-oriented drives, which can also be integrated into the parameterization of DDM. This is because DDM merges different preference-influencing factors (pavlovian, habit, and goal-oriented, to be exact) together into a singular subjective value (Rangel et al., 2008), which is later processed as evidence accumulation to reach the decision boundary. Therefore, the value-based decision-making framework functions as a generic theoretical framework for media selection studies by integrating, comparing and testing different verbal theories concurrently. With that said, it is possible to separate these three preference-influencing factors. For instance, future studies could fit a DDM with time-varying evidence to investigate the extent to which automatic and uncontrolled, or highly controlled processes guide media selection (Diederich & Trueblood, 2018; Roberts & Hutcherson, 2019). This is what we mean when we say that computational models are generative. It was previously impossible to test this MMT assumption. But now, this assumption can be tested, and media selection theory can be refined.

Alternatively, the DDM may be questioned in terms of its utility as an ideal decision-making model under which to examine media selection. Media selection is, after all, rarely a binary choice between repeated alternatives. Research using binary choice decision tasks has also shown a dependency between chosen and unchosen options. Over time, the value of unchosen options is down weighted relative to the value of chosen options such that repeatedly choosing one type of option negatively reinforces selection of a different type of option (Biderman & Shohamy, 2021). Admittedly, DDM and the two-choice decision task lack a certain level of generalizability and external validity because they inadequately simulate and approximate real-world media selection scenarios. Real-world media selection behavioral data requires tailored complex behavioral modeling such as a multivariate version of DDM for multi-alternative choice tasks (Krajbich & Rangel, 2011), reinforcement learning models combined with a probabilistic function for media engagement (Fisher & Hamilton, 2021), or random walk models for sequential media selection (Lydon-Staley et al., 2020). However, despite its low generalizability, DDM is still a valid and sufficient methodology to reveal people's preference for hypothetical media content, and can be used to explain (why) media selection process under an algorithmic (what) and implemental (how media selection phenomenon relies on biological process) level (Huskey et al., 2020).

Our study shows just how much can be learned by simplifying the decision landscape and that the mathematical simplicity necessary to formalize a verbal model is heuristically provocative, a theoretical contribution in its own right (DeAndrea & Holbert, 2017). Additionally, formalizing dynamic, complex, and multichoice decision making is notoriously non-trivial, although state-of-the-art approaches are beginning to emerge (Yoo et al., 2021). We offer a starting point from which others may design and test their own media selection models (for an extended theoretical treatment, see Gong & Huskey, in press).

Conclusion

In conclusion, we argue that inconsistent conceptualization via verbal models of media choice may have insufficiently specified the role of valence and arousal on media selection processes. If we evaluate verbal models of media choice, such as MMT, based on established criteria for evaluating theory in communication science (DeAndrea & Holbert, 2017), it is clear from our own data that past verbal models may lack explanatory power in terms of accurately depicting media choice behavior. We argue that this lack of explanatory power likely stems from the multiple definitions used to describe affect, arousal, and selection in past work, which makes MMT's hypotheses nearly impossible to falsify. In contrast to past work, by fitting a computational model (HDDM), we were able to demonstrate that MMT's valence hypotheses are fully falsified, and its arousal hypothesis is partially falsified. Therefore, our work helps to improve verbal theories of media choice by increasing falsifiability. In addition, we hope to increase the accuracy and explanatory power of these models by including previously unaccounted for boundary conditions.

How can we be confident our findings may argue against a 35-year-old theory? Using a method that depends on computational power and cognitive understanding of decision-making that were not present 35 years ago when MMT was formulated, we were able to more accurately specify under which conditions specific propositions received support, as well as identify a previously undiscovered mechanism, response caution, as central to affect-driven media selection processes. Thus, our contribution is a timely update to the theory, based on understanding media selection as a value-based decision-making task under specific conditions. However, we would also note that our study does not reduce the undeniable heuristic provocativeness or organizing power of MMT. Indeed, we identify that affect and arousal are powerful determinants of media choice under specific decision-making conditions. We hope that our work drives further interest in value-based decisions making tasks across communication subfields beyond media choice.

Finally, our work is in line with calls for communication scientists to create theory which can be specified at computational (why does a behavior exist), algorithmic (what mathematical rules govern the behavior), and implementation (how is that behavior biologically implemented) levels of explanation in order for the field to progress as a science (Huskey et al., 2020). Formal models, which exist at the algorithmic level, connect the computational and implementation levels. Communication research has made great strides explaining and describing behavior at computational and implementation levels separately. Formal models have the capacity to clearly and unambiguously link these levels (for an example, see Wang et al., 2015). Using formal models allows communication scientists to bridge individual and group level processes studied at the different levels of explanation, that is, they are scalable. The individual-level phenomena of interest to communication researchers may be directly connected via formal modeling to group-level phenomena of interest (Fisher & Hamilton, 2021; Wiradhany et al., 2021). We join the effort (e.g., Chung et al., 2012; Chung & Fink, 2022; Fink, 1993; Huskey et al., 2020; Wang et al., 2006, 2011, 2015) to move communication science in this direction.

Citation diversity statement

Citation disparities exist in communication research (Chakravartty et al., 2018; Trepte & Loths, 2020; Wang et al., 2021). We quantify our citation practices by including a citation diversity statement (Supplementary Section 16; Zurn et al., 2020).

Supplementary material

Supplementary material is available at *Journal of Communication* online.

Notes

1. MMT was originally called the "theory of affect-dependent stimulus arrangement" and is part of a broader body of work which suggests that media selection is a function of the affective state of media users and that selection will follow the principle of mood optimization (Reinecke, 2016).
2. It should be possible, in principle, to test the intervention potential and semantic affinity hypotheses using DDM. Doing so requires developing reliable and valid manipulations for variables related to these hypotheses, and verifying that these manipulations can be done in a way that is invariant across a large number of trials.
3. Unlike frequentist approaches to null-hypothesis significance testing (NHST), Bayesian inference eschews "significant/not-significant" language in favor of "credible/not-credible" language. Whereas NHST conventionally specifies $\alpha = .05$ as the threshold for a "significant" result, there is not a conventional cutoff that demarcates a "credible" result from a "not-credible" result, at least when conducting inference on the posterior probability distribution as we do in this manuscript. Some HDDM studies set relatively liberal thresholds for a "credible" result (e.g., 90%, see Eikemo et al., 2017). In our case, and given the confirmatory nature of our project, we have adopted a stricter threshold of 97.5%, which is roughly equivalent to a two-tailed NHST at $\alpha = .05$. A complete treatment of Bayesian inference on a posterior probability distribution is beyond the scope of our current paper, but we direct interested readers to Kruschke (2013), which details the inferential approach used in our project.

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