



Consider the time dimension: theorizing and formalizing sequential media selection

Xuanjun Gong ^{1,2,*} Richard Huskey ^{1,3,4}

¹Cognitive Communication Science Lab, Department of Communication, University of California, Davis, CA, USA

²Department of Statistics, University of California, Davis, CA, USA

³Cognitive Science Program, University of California, Davis, CA, USA

⁴Center for Mind and Brain, University of California, Davis, CA, USA

*Corresponding author: Xuanjun Gong. Email: xjgong@ucdavis.edu

Abstract

Existing media-selection theories predominantly consider media selection at a static moment-in-time. However, such theorizing is out-of-step with today's media landscape, which is dominated by sequential media consumption where future media selection is dependent on previously selected media. Ignoring the dependencies among sequential media selection leads to a failure to theorize and model the time-evolving nature of media selection. To bridge this gap, we review computational modeling methods and offer an integrative theoretical framework for studying sequential media selection. In doing so, we lay the theoretical and methodological foundation necessary for state-of-the-art research focused on understanding the underlying mechanisms of, and sequential dependencies among, media selection. Our sequential media-selection framework helps media researchers by theorizing and formalizing processes related to learning, exploration vs. exploitation, and foraging. The outcome is a manuscript that builds on existing theory and research to offer a roadmap for next-generation media-selection inquiry.

Keywords: media selection, computational modeling, reinforcement learning, exploration/exploitation, foraging.

Media shapes people's minds (Weber et al., 2015; Schmälzle, 2022), psychological well-being (Ostic et al., 2021; Xu et al., 2016), beliefs (Anspach & Carlson, 2020; Veenstra et al., 2014), and behaviors (Nabi & Oliver, 2009), as well as society more broadly (Perse & Lambe, 2016). People's selective exposure to content determines how media influences audiences. Thus, it is crucially important to understand how and why people select different types of media. This is because a better understanding of media selection helps researchers and practitioners generate more effective campaign strategies, more accurate estimates of media effects, and more comprehensive understanding of the media economy more broadly. In summary, if we are going to understand the causal process of media content → media reception → media effects (Schmälzle & Huskey, 2023), then we must understand how and why people select media in the first place.

Existing theories explore how media content and audience characteristics impact media selection. These theories almost universally specify media selection as a singular, snapshot, decision-making event (Figure 1A). Research within this paradigm has revealed hard-won insights into mechanisms that govern media selection (for a review, see Hartmann, 2009). At the same time, we know that media selection happens in a dynamic environment, and that media preferences systematically vary over time (Shade et al., 2015). Therefore, any mechanistic explanation of media selection that does not consider the time dimension is necessarily incomplete.

To bridge this gap, we theoretically integrate well-documented mechanisms of media selection with decision theoretic models of sequential choice (Figure 1B). Our article begins by briefly reviewing existing frameworks for studying static media selection with a particular focus on well-studied

mechanisms. Subsequently, we consider how these mechanisms can be extended to account for sequential media selection using five different decision theoretic computational models: *Markov chain* (MC) and *Markov decision process* (MDP), *reinforcement learning* (RL), *exploration exploitation* (EE), and *optimal foraging theory* (OFT). In these sections, we pay particular attention to each model's assumptions and how these assumptions unlock new ways of studying sequential media selection. We conclude with suggestions for researchers looking to develop and test new theories using these computational approaches.

Content and audience characteristics govern static media selection

Media selection theories consider people's media choice as a static selection problem (Sears & Freedman, 1967); that is, why people prefer one type of media content over alternatives in a static decision-making scenario. This process is typically understood as a type of *selective exposure*. Selective exposure is a rather broad term that has been explored across a number of different domains (for reviews, see Knobloch-Westerwick, 2014; Sears & Freedman, 1967). Therefore, we draw on a narrower definition and characterize selective exposure as media selection "behavior that is deliberately performed to attain and sustain perceptual control of particular stimulus events" (Zillmann & Bryant, 2013, p. 2).

A number of theoretical models have been proposed in order to explain media selection. Among the oldest, mood management theory (MMT) suggests that media selection is a function of people's affective state and media content's affective characteristics (Zillmann, 2000). As a normative theory from a hedonistic perspective, MMT hypothesizes that

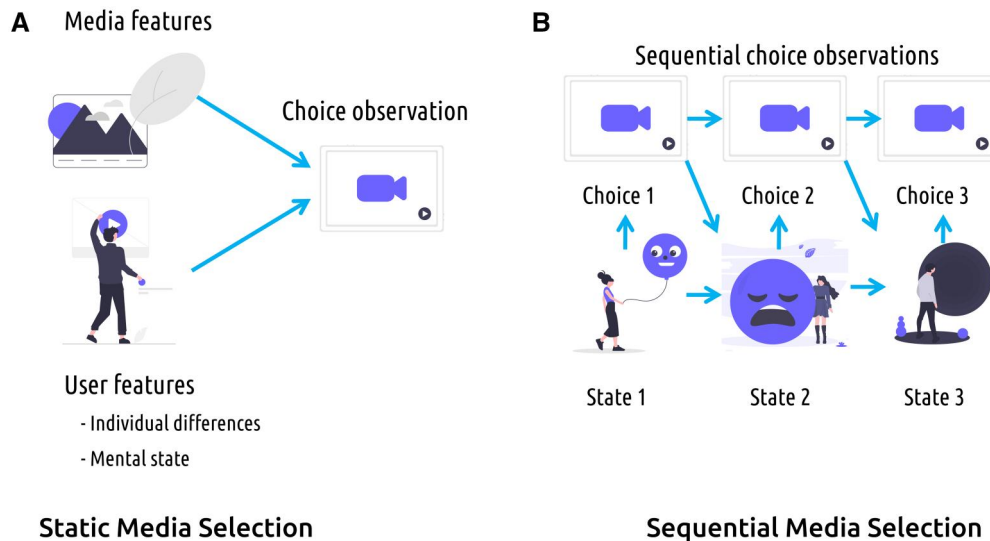


Figure 1. (A) Static media-selection theories suggest that media choices are determined by the interaction between media content characteristics (e.g., valence, arousal, information utility, media use) and audience characteristics (e.g., gender, mood, gratifications sought). (B) Theorizing sequential media selection suggests that media choices are also heavily dependent on previously chosen choices. Specifically, previous media choices might change people's mood state, help people learn the expected value of a specific type of media option, induce boredom, elicit a bias against choosing similar media options, and guide people to explore novel media messages. A key distinction between static media selection and sequential media selection is that sequential media selection considers the time dimension of media choices and aims to understand the temporal dependencies among sequential media choices.

humans are rational optimizers of pleasant feelings; therefore, people choose media content that maximizes happiness. Decades of research demonstrate that affective characteristics (i.e., arousal, valence) shape people's media selection, but in ways that somewhat deviate from MMT's original hypotheses (Carpentier, 2020; Gong et al., 2023; Nabi, 2020).

Besides affective characteristics, Atkin (1973) suggests that information utility, referred to as the perceived usefulness of information for fulfilling a goal, largely determines media selection behavior. Different from the hedonistic perspective, information utility theory adopts a utilitarian framework and argues that information-seeking media selection is driven by extrinsic motivation. Supporting these claims, informational features explain people's news consumption and health message exposure (Knobloch-Westervick et al., 2005). Moreover, intrinsic motivations for autonomy, competence, and relatedness appear to govern people's media selection behaviors (Reinecke et al., 2012).

Collectively, these theoretical explanations demonstrate that media content (e.g., affect, utility) and audience characteristics (e.g., affect, motivation) govern media selection.¹ However, the integrative linkages between these theoretical explanations are not immediately clear as they are usually investigated independently rather than under a common theoretical and analytical framework.

Meta-theoretic frameworks suggest computational models govern media selection

Uses and gratifications (U&G) is a framework for integrating content and audience characteristics (Katz et al., 1973). U&G suggests that individuals are goal-oriented and driven by specific needs and gratifications, which are actively sought from media (Ruggiero, 2000). These needs and corresponding gratifications can be categorized into multiple classes, including cognitive needs, affective needs, personal identity,

social interaction, escapism, and habitual needs (Katz et al., 1973). Insightfully, U&G recognizes that individuals are gratification seekers and needs satisfiers who choose media content that is expected to optimally satisfy perceived needs (Jensen & Rosengren, 1990; McQuail, 1997). This hints that people select media based on an internal algorithmic model that estimates anticipated gratifications from different media options based on an individual's needs.

Unlike U&G, which uses a discrete categorization of media gratifications, expectancy value theory (EVT) suggests that media choices are determined by the expected value of media options (Fishbein & Ajzen, 1975). Expected value is a function of the estimated likelihood of instrumental and experiential outcomes multiplied by the subjective valuation of each outcome. Thus, EVT offers an algorithmic explanation of media selection that maps perceived media features with an individual's internal mental states into a singular valuation. Crucially, both U&G and EVT verbally specify, but never computationally formalize, the algorithmic steps that govern the generative process of granular media selection behavior. Computational models (Guest & Martin, 2021; Smaldino, 2020) are one way of mathematically formalizing an algorithmic model.

Initial theorizing (Fisher & Hamilton, 2021) has computationally formalized the algorithmic models that govern media selection as a type of value-based decision making (Rangel et al., 2008). Value-based decision making involves three stages—option representation, option valuation, and option selection. In media selection contexts, media options are represented as a set of content characteristics (e.g., affect, utility), which are evaluated depending on a set of audience characteristics (e.g., affect, motivation). A valuation function integrates these characteristics to form a singular subjective value for each option such that higher value indicates stronger preference (Figure 1A; Levy & Glimcher, 2012).

Subsequently, the subjective values for each option are compared. This comparison yields an outcome such that the higher value media option, or the option that will result in greater reward, has a higher probability of being selected (Gong & Huskey, in press).

Integrating verbal theories and computational models to explain static media selection

It is possible to integrate existing media-selection mechanisms with computational value-based decision-making models. Let us begin by specifying a domain-general valuation function (Equation 1; Roberts & Hutcherson, 2019). We then account for existing media-selection mechanisms that specify content and audience characteristics by including each as terms in the function.

$$V(F, S) = \beta_1 F + \beta_2 S + \beta_3 F * S. \quad (1)$$

In this function, the subjective value (V) of a media option (e.g., a movie) is a function of an individual's perceptions of a media option's features (F ; content characteristics) and an individual's current state (S ; audience characteristics). How should we operationalize the parameters in this function? We can turn to existing theory for answers. For example, MMT specifies how affective (operationalized in terms of arousal and valence) media features and an individual's affective state together explain media selection. Drawing on MMT, it is possible to express the value people attribute to a given media option as a linear combination of affective characteristics of media content features and the audience's current mood state (Equation 2).²

$$\begin{aligned} V_{\text{option}} = & \beta_0 + \beta_1 \text{MovieValence} + \beta_2 \text{MovieArousal} \\ & + \beta_3 \text{MoodValence} + \beta_4 \text{MoodArousal} \\ & \beta_5 \text{MovieValence} * \text{MoodValence} \\ & + \beta_6 \text{MovieArousal} * \text{MoodArousal} + \varepsilon. \end{aligned} \quad (2)$$

After media options are evaluated by the subjective valuation function (e.g., Equation 2), people are expected to select the media option, from an array of options, with the highest subjective value. In the simplest case, a two-choice decision, it is possible to formalize this as:

$$\text{MediaSelection} = f(V_{\text{optionA}} - V_{\text{optionB}}). \quad (3)$$

As a first start, this exact formalization of MMT has been empirically tested (Gong et al., 2023) using a computational drift diffusion model (DDM; Ratcliff, & McKoon, 2007). However, one core limitation of this project, and the DDM more generally, is that each choice is represented as a static decision. In what follows, we discuss how to account for the time dimension.

Theorizing and computationally modeling sequential media selection

People's media selection depends on previously selected media (Gong & Huskey, 2023). In fact, people's media selection, such as music listening, web browsing, Wikipedia reading, and social media engagement can be explained and predicted by people's previous media-selection histories (Gong & Huskey, 2023; Lindström et al., 2021; Lydon-

Staley et al., 2020; Tria et al., 2014). Existing theory and research largely ignores this temporal dependency. Therefore, our understanding of people's media selection is necessarily incomplete. In this section, we discuss approaches that account for temporal dependencies in media selection and provide theoretical extensions that increase our understanding of people's sequential media selection.³

As previously demonstrated, people's media selection can be understood as a value-based decision-making process where the value of media options is a function of media content and audience characteristics (Equation 1). Arguably, audience characteristics, particularly an individual's mental state, are not stationary but instead vary from decision to decision, and are influenced by preceding media choices. For example, MMT proposes that media selection depends on people's mood state and media's affective features. Importantly, previously selected media may influence an individual's mood state, which will consequently influence their subsequent evaluation of media options and impact their subsequent media selection (Figure 1B). This temporal dependency between media effects and media selection (Fisher & Hamilton, 2021) lays the foundation for our argument about sequential media selection.

In order to understand sequential media selection, we need to clearly specify its dynamic nature. Accordingly, we define sequential media selection as a series of media decisions where (1) the decisions are not independent and (2) the state of the decision-maker changes as a consequence of previous choices (Brehmer, 1992). Formally, sequential media choices can be defined as a sequence: $\langle C_1, C_2, \dots, C_t \rangle$, where C_t denotes the media choice C at time t . We can also define the temporal dependency between sequential media choices as follows:

$$P(C_t | C_{t-1}, C_{t-2}, \dots) \neq P(C_t). \quad (4)$$

This shows that the conditional probability of choosing an option at a specific time point (C_t) depends on previous choices (C_{t-1}, C_{t-2}, \dots) and, therefore, is not equal to the marginal probability of choosing the option $P(C_t)$. Said differently, the probability that an individual will select a given media choice in a static media-selection context is not the same as the probability that an individual will select a given media choice in a sequential media-selection context.

This dynamic structure of sequential media choices can be described in semantic and temporal dimensions. In the semantic dimension, researchers study the semantic distribution of *what* people choose in a choice sequence. For instance, someone listening to music might choose to listen to a semantically similar (e.g., song from the same artist) or dissimilar (e.g., song from a different artist) song relative to previously listened-to songs. This behavior has been explained using a novelty-driven probability model (Tria et al., 2014). In the temporal dimension, researchers can study the temporal distribution of *when* people choose a specific media option. For instance, the time frequency of people's social media posting can be explained by the amount of social rewards (e.g., number of "likes") received from previous posts, such that the more "likes" people receive, the faster people will make their future posts (Lindström et al., 2021).

In general, semantic dimensions of sequential media choices answer questions about what is selected, and the temporal dimension answers questions about when selection

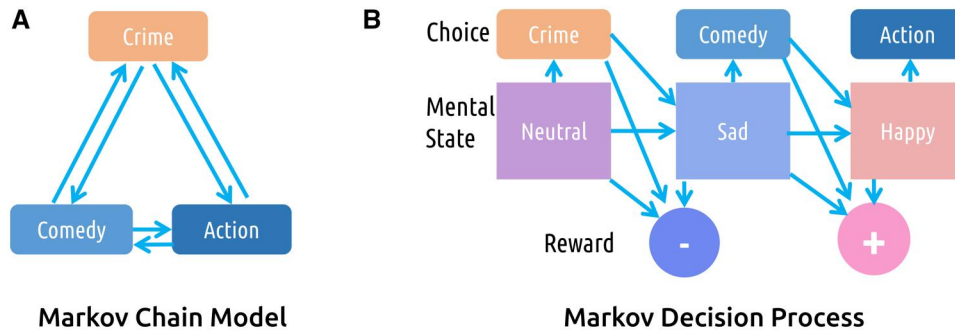


Figure 2. The MC model (A) assumes that future media choices are only determined by the immediately preceding media choice. For instance, considering three media options (i.e., crime movie, comedy movie, action movie), the MC model will quantify the conditional transition probabilities of choosing a crime movie after having watched a comedy movie or action movie. By comparison, the MDP model (B) adds the additional assumption that media choices are determined by the inner state of the decision maker. Therefore, the MDP assumes that previous media choices and the inner states together determine the obtained reward (outcome) from media consumption, which is expected to be optimized by sequential media-selection behaviors. This figure gives the example of a media user in an initially neutral mood state. After watching a crime movie, the media user becomes sad and therefore obtains a negative reward outcome. Subsequently, the media user decides to watch a comedy movie, which results in a happy mood state and a positive reward outcome. This process continues for subsequent selection.

occurs. Both can be computationally modeled as a value-based decision-making process. The next question is how can we model the time-varying dependency of sequential media choices?⁴ There are two main approaches in the decision-making literature to address this question: descriptive models and normative models (Bell et al., 1988). Descriptive models are a data-driven approach aiming to model what people actually choose. These are particularly useful for theory generation. On the other hand, normative models assume that people are value optimizers, and thus aim to answer selection questions after accounting for cost/benefit tradeoffs. Unlike descriptive models, normative models are confirmatory in nature, and require strong hypotheses. Drawing from both approaches, we now propose several models for investigating sequential media selection.

Descriptive modeling: MC and MDP

The model and its assumptions

We have demonstrated the dependency between media effects and media choices that governs sequential media selection. MC models (Vermeer and Trilling, 2020) are one way of accounting for this dependency, with some simplifying assumptions. Instead of modeling all prior media selection (as in Equation 4), MC models assume that media selection (C_t) depends only on the immediately preceding choice (C_{t-1}), as shown in Equation (5).

$$P(C_t|C_{t-1}, C_{t-2}, \dots) = P(C_t|C_{t-1}). \quad (5)$$

This simplifying assumption accounts for the media effect/subsequent-choice dependency described above. How? In short, the probabilistic distribution of an individual's current selection (e.g., watching a crime movie) is assumed to depend only on the previously selected media option (e.g., previously viewed movies; Figure 2A). Therefore, the stochastic transition process between media choices can be descriptively modeled by the conditional probability $P(C|C')$, indicating the transition probability from choice C' to C . Empirically, this MC framework has been successfully used as a descriptive model for a set of complex sequential human behaviors, including people's sequential media selection (Gong & Huskey, 2023).

One limitation of MC models is that they do not explicitly account for the interaction between selection and the effect (the psychological state resulting from a choice). MDP (Figure 2B; Sutton & Barto, 2018) address this limitation by specifying three interactive components: choice (C), state (S), and a reward function of the coupled choice and state ($Q(C, S_t)$). In detail, the reward function is defined as the expected value (E) of reward (R_t) after choosing an option (C) given the current state (S_t ; Equation 6). The option (C_t) that maximizes the reward function will be chosen (Equation 7), which results in a future state (S_{t+1}) and state transition probability ($P(S_{t+1})$; Equation 8).

$$Q(C, S_t) = E(R_t | C, S_t). \quad (6)$$

$$C_t = \operatorname{argmax}_C (Q(C, S_t)). \quad (7)$$

$$P(S_{t+1}) = P(S_{t+1}|S_t, C_t). \quad (8)$$

Unlike MC that specifies the choice distribution as governed by the conditional probability $P(C|C')$, MDP suggests that the choice distribution is determined by both previous choices and previous states, governed by a reward function, and the state transition probability.

The model as applied to sequential media selection

How might this approach be used to examine sequential media selection? Consider a scenario with three media options (e.g., comedy, crime, affectively neutral). A simple MC model could be used to estimate the sequential movie selection process as shown in Figure 2A. In this example, the MC model will analyze the sequential dependencies of media selection by estimating the conditional transition probabilities, such as the probability of watching a crime movie after watching a crime movie, comedy movie, or action movie. This content-focused data-driven approach may serve as a foundation for theory building. If consistent transitions are observed across a range of media, then it may be possible to theorize generalizable mechanisms that account for, or explain, these transition probabilities (Vermeer & Trilling, 2020).

As an extension of the MC model, the MDP model accounts for audience (state) characteristics in addition to content characteristics. Let's return to our movie selection example. At each timepoint, an individual needs to estimate their current mood state (e.g., happy), as well as how much reward can be obtained from available movie options (e.g., crime movies) and the mood state that will result from selecting a given movie option (e.g., sad). We might expect, therefore, that people will select the movie option that they estimate will result in the best possible reward outcome (Figure 2B). What theoretical mechanisms govern these outcome estimations? We might turn to existing theories suggesting that people are hedonistic or utility maximizers. Alternatively, the MDP model might provide a foundation for computationally formalizing to the growing body of literature examining emotional trajectories (e.g., Keene & Lang, 2016; Wang & Bailey, 2023) or flows (e.g., Nabi & Green, 2015) during media use.

Normative modeling: reward learning and generalization

The model and its assumptions

One unanswered question arising from the previous section is, during sequential media selection, how do people know which option leads to the optimal outcome? Answering this question requires media users to *learn* and *update* the reward (Q) function to control the transition policy and reach an optimal outcome based on their previous media selection. How does this learning happen? This question has at least two possible answers, both of which normatively treat people as value optimizers. The first specifies how current reward estimates are updated based on instances where the same choice was previously selected. This is known as RL. The second approach, reward generalization, updates current reward estimates based on instances where a different choice was previously selected.

Q-learning is a well-known RL process (Watkins, 1989; Watkins & Dayan, 1992), which uses a temporal difference (TD) algorithm (Sutton & Barto, 2018) to update the reward (Q) function. This TD learning process has been well documented, empirically tested, and applied across a wide range of applications (Niv, 2009; Watkins & Dayan, 1992). In the sequential media-selection domain, the Q-learning process has been suggested as the media effect that governs subsequent media choices (Fisher & Hamilton, 2021). Importantly, this RL process helps people optimally control their subsequent choices and inevitably introduces a reinforcement mechanism for their sequential behaviors. Simply put, people tend to repeat high-reward choices and avoid low-reward choices, recognizing that reward may diminish with repeated selection of the same choice (Figure 3A). Media users may use this TD-based RL model to make sequential media choices, where the reward function (Q_t) is independently updated after experiencing reward (R_t) for selecting a given option (C^*) and governed by the learning rate parameter (α ; Equation 9).

$$Q_{t+1}(C^*) = Q_t(C^*) + \alpha(R_t - Q_t(C^*)). \quad (9)$$

However, options in sequential media selection often include novel content; that is, media options that have never been experienced before. In TD-learning, the reward value (R_t) of media options (C_t) can only be estimated if an option

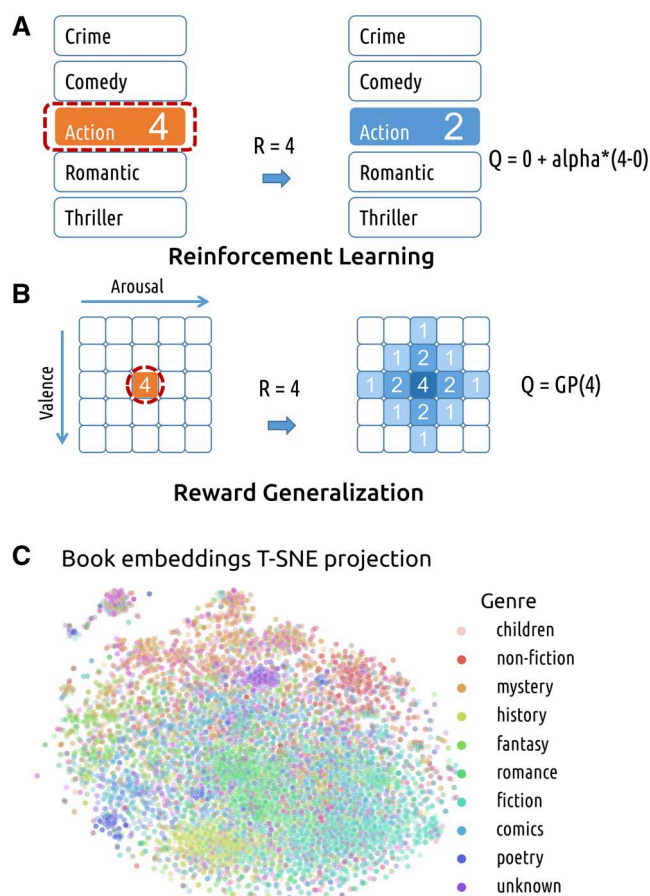


Figure 3. RL models specify that people can learn from previous media-selection experiences. For example, consider an individual selecting from different movies that vary in valence and arousal. Conceptually, each movie can be represented as a cell in a discrete array of genres or a two-dimensional matrix that encodes valence and arousal. For RL (A), each movie choice is associated with a specific reward outcome. After choosing a movie and obtaining a high reward outcome, an individual learns that this movie is likely to elicit a similar reward on subsequent rewatching. However, the magnitude of this reward may be reduced each time the movie is rewatched. For reward generalization (B), the individual is able to make estimations about the reward value associated with other unwatched movies such that similar unwatched movies are likely to generate a reward similar to the watched movie. Importantly, however, the expected reward magnitude of unwatched movies decreases as the similarity from the watched movie decreases. Media options can be represented as data points in a semantic space (C) depending on research questions and theoretical framework. For instance, books can be embedded in a high-dimensional semantic space constructed using the book summaries. Incorporating a transformer language model, books can be embedded in a 381-dimension space (reduced to two dimensions using principal component analysis) in a way such that similar books are close to each other while dissimilar books are further away from each other.

has been experienced before. Without satisfying this requirement, the TD-learning algorithm cannot estimate the reward function (Q_t). Thus, a media user needs an alternate approach for estimating the reward of novel options.

One solution for solving this problem is to infer the reward of a novel option by generalizing from the reward of a known option (Figure 3B; Wu et al., 2018). A common method to deal with the reward estimation of novel options is to use a function approximator, instead of an exact matching of given options and previous choices (Tesauro, 1992). Thus, similar to the value function for static media decisions proposed in

Equation (1), it is possible to specify the reward function (Q) as the expected value (E) of a linear function (Equation 10; Mnih et al., 2013) of state features (F_s) and choice features (F_c).

$$Q(C, S) = E\left(\sum \beta_c F_c + \beta_s F_s + \beta_{c,s} F_c F_s\right). \quad (10)$$

In this model, β is the free linear coefficient for each parameter. This approximation function informs the reward function (Q) for the unknown media option based on the similarity of its features to a known media option's features. The assumption is that similar media options yield similar rewards and dissimilar options yield dissimilar rewards.

Equation (10) specifies a linear approach for reward generalization, but nonlinear approaches are also possible (Equation 11). In fact, research demonstrates that people use a nonlinear Gaussian Process model to generalize the reward of a known option to a novel option (Schulz et al., 2019; Wu et al., 2018). Formally, the Gaussian Process (GP(\cdot))⁵ model generalizes the reward of known options ($Q(C)$) to novel options ($Q(C^*)$), based on feature similarity between options $k(C^*, C)$.

$$Q(C^*) = \text{GP}[Q(C), k(C^*, C)]. \quad (11)$$

The model as applied to sequential media selection

How might we use RL and reward generalization models to explain sequential media selection? Consider an individual making sequential decisions on which movie to watch. The RL model could be used to demonstrate the sequential selection of different movie genres (e.g., action, comedy, action, romantic, thriller) as shown in Figure 3A. After watching an action movie, the individual updates their estimate of the reward value of action movies as regulated by the TD-learning algorithm. If a high reward value is experienced after watching the action movie, the reward function for action movies will increase. If a low reward value is experienced, the reward function will update the estimate of action movies correspondingly. With this normative RL mechanism, an individual can gradually optimize their selection strategy by adjusting their sequential movie selection based on previous experiences. This hypothesis has not yet been empirically tested in sequential movie selection contexts. However, this hypothesis has received support in social media contexts such that an RL mechanism appears to govern the frequency of social media posting (Lindström et al., 2021).

Distinct from the RL model, which considers movies to be embedded in a discrete space (like genres), reward generalization assumes that options are embedded in a continuous high-dimension space. As a result, reward generalization is capable of explaining sequential media selection with higher granularity because reward estimates can be extended to unknown options based on the similarities between options. For instance, as shown in Figure 3B, assuming movies are embedded in a two-dimensional space (i.e., valence and arousal), after experiencing a specific movie choice (neutral valence and moderate arousal) with high reward, the reward generalization mechanism will update reward estimates of every possible option with the Gaussian process function, in a way such that similar movie options (with respect to valence and arousal) will increase to a higher extent, and dissimilar movie options will increase to a lower extent.

In practice, media options are likely embedded in a high-dimensional space that extends beyond arousal and valence. This would certainly be consistent with existing theorizing (e.g., information utility, hedonism, U&G). Reward generalization is sufficiently flexible to account for this high-dimensional space (Figure 3C). As a result, this normative model provides a mechanistic account for *how* people make sequential selections that integrates with existing theoretical explanations for *why* people select sequential media choices in a reward-optimizing way.

Normative modeling: exploration vs. exploitation The model and its assumptions

Importantly, learning processes, including RL and reward generalization, are unable to fully resolve difficulties associated with estimating the reward of novel options. This is particularly true in new or uncertain contexts. Media content are constantly changing (e.g., new music albums, new moves, new streaming videos, or breaking news). Thus, the difficulty of state estimation and choice estimation grows as time goes by.⁶

To ensure optimal media selection in a changing and uncertain world, media users need to frequently sample novel and uncertain media options. This sampling aids in learning and reduces uncertainty associated with novel media. Media users face a tradeoff between consuming known media and unknown media. More specifically, this tradeoff is between choosing currently known options with high reward through reinforcement or generalization (exploitation) and sampling unknown options with high uncertainty (exploration). This is known as the famous exploration vs. exploitation (EE) dilemma in Figure 4A (Daw et al., 2006; Sutton & Barto, 2018).

The basic idea of the EE dilemma is that, at any given moment, the optimal strategy for the highest reward is to exploit the most rewarding choice (*exploitation*); however, it is still necessary to regularly explore alternative options (*exploration*) in order to gain information about the environment (Cohen et al., 2007; Daw et al., 2006). Consider a simple example, choosing a song to listen to. A person might listen to their favorite song from their favorite artist (*exploitation*) or might listen to a new song from that artist's latest album (*exploration*). Selecting the new song is associated with a level of uncertainty about the outcome (will the person like or dislike the new song). However, selecting the new song also helps the individual obtain knowledge about the new song and the artist. Both pieces of information are vital for guiding future selection.

There are two strategies for addressing the EE problem. The first strategy is random exploration, which requires the decision maker to make a random choice within the option space (Watkins, 1989). An example of random exploration is making choices based on a softmax function (similar to Equation 7) of expected rewards (Equation 12). Here, higher value options have a higher probability of being chosen. The parameter β determines the rate of exploration by controlling the spreading of the probability distribution of choices. Exploration is maximized when $\beta \rightarrow 0$, which results in a uniform distribution where all options have equal probability of being selected. By comparison, exploitation occurs as when $\beta \rightarrow \infty$. This results in a deterministic distribution where only the highest reward option is selected.

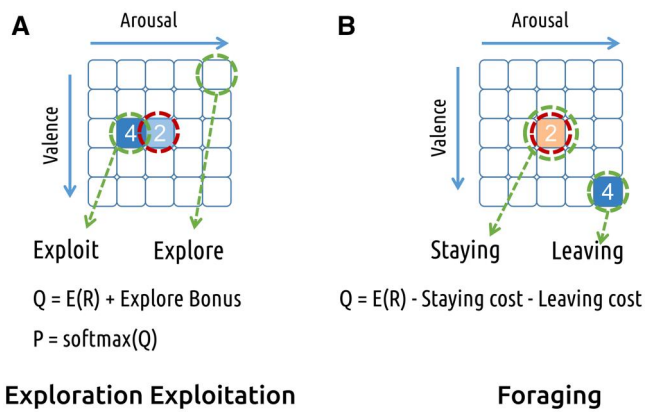


Figure 4. The EE model (A) addresses the dilemma between choosing a well-known high reward media option or choosing a novel media option. For example, a rock music fan might choose to listen to classical music due to curiosity and exploration motivation. By comparison, foraging models (B) specify an individual's need to balance between staying in the current media patch or leaving to a distant media patch. For example, after listening to their favorite album by their favorite musician, an individual might listen to a new album by a new musician in order to counteract boredom and minimize potential fatigue with their favorite musician's album.

$$P(\text{Selecting option } k) = \frac{\exp(\beta V_k)}{\sum_{i=1}^n \exp(\beta V_i)}. \quad (12)$$

The second strategy is directed exploration, where the decision maker makes choices with a bias toward novelty, uncertainty, and information (*exploration*; Gittins, 1979). This approach can be implemented by adding an information bonus to the reward function (Q); which was first introduced in Equation 6). A well-known algorithm is the upper confidence bound (UCB) algorithm (Auer et al., 2002), which adds a term that is linearly related to the uncertainty (v) of options relative to the reward (Q) function. Thus, the updated reward (Q) function can be expressed as in Equation 13), where γ represents the linear parameter controlling exploration. As $\gamma \rightarrow \infty$ bias toward the exploration of uncertain choices increases.

$$Q(C_t, S_t) = E(R_t | C_t, S_t) + \gamma v_c. \quad (13)$$

The model as applied to media selection

A common way to study the EE problem is with a two-armed bandit task (Sutton & Barto, 2018). In this task, participants sequentially choose from one of two gambling machines, each with a different probabilistic reward function. Completing the task requires participants to balance exploitation (choosing the machine with the highest expected reward) and exploration (choosing the machine with the highest uncertainty). Research shows that people use the UCB algorithm to guide their selection in lab-based bandit tasks (Wu et al., 2018) and real-world sequential selections (Schulz et al., 2019). Therefore, we hypothesize that people's sequential media behaviors will also follow this exploration strategy, such that people are biased toward high-uncertainty media options.

In media contexts, this exploration–exploitation strategy has already proven to be successful in recommending news (Li et al., 2010) and music (Wang et al., 2014). Moreover,

preliminary results on observational music listening data already suggest that people use the UCB algorithm during sequential music selection (Gong & Huskey, 2022). This finding could be experimentally confirmed using a bandit-style task. In this example, a participant might be asked to sequentially choose between a known song (exploitation) or a novel song (exploration). Their choice data would then be fit using the random and UCB models. The better fitting model would be selected as the one that best explains the exploration/exploitation strategy used (Vandekerckhove et al., 2015).

This approach could be extended to see if the UCB algorithm governs different types of media selection (e.g., do people show a similar bias toward novelty when selecting non-music media?). Questions related to genre preference formation and the influence of genre on selection (e.g., Liang & Willemsen, 2021) might be investigated using EE models. Moreover, people's media task-switching and multitasking behaviors have also been found to be determined by the EE trade-off mechanism (Fisher & Hamilton, 2021; Wiradhany et al., 2021). In sum, the EE dilemma may prove quite generative for future sequential-media-selection research.

Normative modeling: OFT

The model and its assumptions

An alternative approach to solve the EE problem is proposed by OFT (Pyke, 1984). OFT describes a *patchy* environment. A *patch* represents a resource, with varying levels of reward, that can be repeatedly selected. The reward associated with selection within a given patch is called the *foraging rate*. In this environment, individuals must sequentially choose to exploit a current patch or explore a new patch (Figure 4B). The critical difference between OFT and EE is that OFT recognizes that continued exploitation is not without cost (e.g., the resource is consumed, the resource becomes less rewarding over time). At the same time, sampling a new patch is not without cost (e.g., energy, risk, uncertainty, time). OFT provides a solution for addressing this diminishing foraging rate vs. switching cost tradeoff. According to the marginal value theorem, an individual will switch to a new patch when the instantaneous foraging rate of staying in the same patch decreases to be equal to the average foraging rate of the entire environment (Pirolli & Card, 1995; Pyke, 1984).

The marginal value theorem, which mechanistically governs the decision to explore or exploit, can be operationally integrated into the UCB model (Equation 13) by adding two additional terms (Equation 14). The first, $GP(N_c)$ where $GP(\cdot)$ denotes the Gaussian generalization process, punishes the repeatedly chosen options and N_c denotes choice repetition. This term reflects the opportunity cost of staying within a given patch. This second term, $d(C_t, C_{t-1})$ measures the distance (d) between patches.⁷ This term punishes long-distance jumps between choices, thereby reflecting the switching cost.

$$Q(C_t, S_t) = E(R_t | C_t, S_t) + \gamma v_c - GP(N_c) - d(C_t, C_{t-1}). \quad (14)$$

The model as applied to media selection

OFT was originally developed to understand how animals forage for food, but it has been extended into other non-food foraging contexts. For instance, people's information search behavior has been shown to resemble animal foraging

patterns (Pirolli, 2007; Pirolli & Card, 1995). Information foraging theory (IFT), an extension of OFT, conceptualizes information as a resource that is distributed in a patchy way. And, just like OFT, IFT considers how people decide to stay in the current information patch or leave and explore new information patches. Within an information context, the forager's decision to exploit a given information patch is governed by the diminishing reward associated with sequentially selecting a given resource (e.g., people become bored by repeatedly watching the same TV show). Similarly, leaving an information patch is associated with risk and switching costs (e.g., people might choose a low-value option in a distant patch, there is a high cognitive cost when switching to a highly dissimilar patch).

Media researchers have already started using OFT as a framework for investigating how people process media messages (Bailey et al., 2021a), and their decision-making post media exposure (Bailey et al., 2021b). Within sequential media-selection contexts, OFT has been shown to account for people's computer mouse movement (Jaiswal et al., 2020), web-browsing behavior (Goodwin et al., 2012), and web-search behavior (Liu et al., 2010; Pirolli & Card, 1995). A common theme seems to be emerging. When the individuals "stay" in a particular media patch for a long period of time, the reward value from that patch decreases to a point where the reward of staying is comparatively lower than the reward associated with "leaving" for alternative media patches. This mechanism offers an explanation for, and computational formalization of, several theoretical questions, including media boredom, shifting media preferences, and curiosity-driven information seeking.

Discussion

Explaining media selection is one of the oldest areas of inquiry for media scholars. Existing theories usually focus on audience and content characteristics and investigate static media selection in snapshot selection scenarios (Hartman, 2009). Nascent theorizing and empirical work has laid a foundation for understanding sequential selection (e.g., Shade et al., 2015; Wang, 2014; Wang et al., 2006, 2011). Research exploring this important question has not yet reached wide scale adoption. Therefore, and even though today's media landscape increasingly features opportunities for sequential selection, our theory and research has failed to keep up. We know very little about how sequential dependencies govern media selection and largely lack theoretical and empirical frameworks for examining these dependencies. In this article, we articulate fundamental definitions of sequential media selection, showcase theoretical frameworks and computational formalizations for investigating this problem, and demonstrate how our approach can be used to test and extend existing media-selection theory.

Value-based decision-making as an integrative framework

Regardless of whether static or sequential, media selection can be analyzed as a type of value-based decision making (Rangel et al., 2008), where (1) individuals make media choices based on the valuation of given media options, (2) the value of each media option can be estimated using functions that account for audience and content characteristics, and (3) individuals select media in a way that aims to optimize

reward by choosing high-value options and avoiding low-value options. In short, people are expected to probabilistically select the most rewarding media. This value-based decision-making framework is a parsimonious integrative theoretical framework that can coordinate existing empirical media-selection theory and research (e.g., mood management, information utility, intrinsic motivation, U&G) with the larger decision-making literature (e.g., Fisher & Hamilton, 2021). It also provides a rigorous methodology where researchers can formally quantify people's media preferences, evaluate the fit of formal models that explain media selection, and scrutinize sequential media selection in different communication contexts.

This article focuses on content and audience characteristics as mechanistic drivers of value-based decision making. The beauty of specifying sequential media selection in terms of value-based decision making is that it helps integrate disparate literatures, including ones that have not been considered extensively in our article. As one example, we have ignored medium in our theoretical integration. Media richness theory (MRT; Daft & Lengel, 1986) offers potentially fruitful integrative potential. MRT considers how medium characteristics influence communication fidelity (e.g., equivocality, uncertainty) which ultimately governs medium selection. Research has examined how context characteristics and medium affordances influence medium selection and constrain MRT (e.g., Ahn et al., 2022; Davis and Chouinard, 2016; Evans et al., 2017; Fox & McEwan, 2017). With sufficient theoretical development, context characteristics and medium affordances could be cast in terms of value. For instance, the medium affordances of video-conferencing may result in lower equivocality and uncertainty relative to text messaging. But context characteristics also matter. A text message may be more appropriate in a noisy environmental context relative to a video-conference. In terms of value, it could be that value increases as equivocality and uncertainty decrease (medium affordances) and value decreases as environmental noise increases (context characteristics). If so, then it should be possible to integrate these two value estimates in a computational decision function to determine which medium an individual will select. Of course, additional theory building is necessary to integrate context characteristics, medium affordances, and a (as of yet unspecified) computational decision function. Fortunately, a rich empirical literature makes such an integration theoretically possible.⁸

Sequential media selection as MDP

These sequential properties can be simply and descriptively theorized as conditional probabilistic dependencies among consecutive choices; formalized using a MC model. In a more complicated way, under the value-based decision-making framework, sequential media selection can be considered as a MDP, where (1) media choices depend on current value estimates for each media option, (2) the value of options depends on media options (content characteristics) and current mental state (audience characteristics), (3) mental state changes depending on previous media choices, and (4) an individual's aim is to accumulate and optimize rewards from sequential media selection.

Learning and exploration

To optimize long-term rewards from media choices, people need to learn from previous experiences and update their

knowledge for high- or low-reward options. Thus, the temporal dependencies among sequentially selected media can be identified as a process that is constantly learning from previous choices in order to forecast the value of future choices and estimate novel options through reward generalization. In addition, people need to explore novel media options that they are unfamiliar with to obtain knowledge of similar options, compared with making choices of exploiting well-known high-reward options. Finally, people need to make decisions between staying in the current media patch or leaving for distant patches as governed by a foraging mechanism. Thus, people's sequential media choices will balance the benefit vs. cost of staying vs. leaving.

Explaining and predicting complex media behaviors

Computationally modeling communication is not new. Although less common in the discipline, computational models have been applied in a number of contexts (e.g., Chung et al., 2012; Chung & Fink, 2022; Fink, 1993; Huskey et al., 2020; Schramm, 1955), including people's media selection (Wang et al., 2006, 2011, 2014). This is because there are several benefits that come when we use computational models (Guest & Martin, 2021; Smaldino, 2017; van Rooij & Baggio, 2021), especially when investigating domain-general media-selection phenomenon (Fisher & Hamilton, 2021; Gong et al., 2023), and particularly when we consider the time dimension in sequential media selection with complex sequential dependencies between granular media choices. First, the computational models (and their corresponding formal theoretical frameworks) introduced in this study help researchers tackle the complexity of the sequential media-selection process, thereby increasing our ability to explain and predict (Fisher & Hamilton, 2021; Guest & Martin, 2021; Huskey et al., 2020; Smaldino, 2017, 2020; van Rooij & Baggio, 2021). Second, this approach provides a bridge for linking theory and practice. Today's state-of-the-art recommender systems use theory-blind predictive models to provide data-driven media recommendations (Zhang et al., 2020). Although data-driven predictive accuracy seems to be reaching an asymptotic upper bound and there are increasing calls for integrating content and audience characteristics into data-driven predictive models (Tkalcic & Chen, 2015). Studies using computational models that account for the content and audience characteristics that govern sequential media selection can help bridge the gap between academics and the media industry. Third, an integrative value-based decision-making framework with computational modeling provides principled methods (i.e., measuring prediction accuracy of future media choices) to distinguish, compare, and integrate different theories (Hofman et al., 2021), which guides the falsification or updating of existing media-selection theories. Finally, the exploration of complex relationships between theoretical constructs in sequential media selection might promote the discovery of novel constructs and measurements for media behaviors. Recent technological advances generate tremendous empirical media-selection (meta)data (e.g., music listening trajectories on Spotify, watch histories on YouTube) and opportunities for the scientific investigation of the nature of human selection behavior. The modeling methods described in this article will help researchers grasp these opportunities, exploit modern digital media data, and initiate novel research and theorizing.

Conclusion and suggestions

We propose an integrative theoretical framework, value-based decision-making, to investigate the sequential dependencies in media selection. Utilizing this framework, we proposed five mechanisms of increasing theoretical sophistication (MC, MDP, reward generalization, EE, foraging) to explain and predict future media selection based on previously selected media. Of course, the five mechanisms introduced here are surely incapable of fully describing the complete picture of the sequential media-selection processes and should be considered as a primer for initial empirical work. One open question is how well these selection mechanisms generalize to different media contexts. Researchers might naturally ask "which model should I start with?" The answer to this is contingent, at least in part, by the research question and the classic distinction between prediction and explanation (Yarkoni and Westfall, 2017). If data-driven prediction is the primary ambition, then descriptive models (MC and MDP) offer an excellent starting point. Alternatively, if explanation is the primary ambition, we suggest starting with a normative model (RL, EE, and OFT).

Given the domain generality of these models, our intuition is that each should fit rather well. However, we recognize that this is ultimately an empirical question. Generally, these empirical questions can be analytically tested through model building, model evaluation, model comparison with either lab-collected experimental behavioral data or naturalistic observational media choices data from media industries. As a theoretical piece, we do not provide empirical evidence or illustrations for the detailed methodology, but we redirect interested readers to existing methodological works (Daw, 2011; Farrell & Lewandowsky, 2018; Gong & Huskey, in press; Wilson & Collins, 2019;) for detailed explanatory tutorials to develop future studies.

We hope that researchers keep two premises in mind when investigating sequential media selection: embrace stochasticity and eschew stationarity (see also Brinberg & Lydon-Staley, 2023). First, stochasticity is essential for understanding sequential media selection. Why? Media selection is a generative process whereby individuals produce observable media selections that are distributed probabilistically. Treating media selection as a static event ignores the stochastic nature of media selection, but makes statistical modeling via data aggregation (e.g., frequency count, mean) easier. However, these aggregation methods assume choice observations are independent, which violates the sequential dependencies specified in Equation (4). In order to understand the generative mechanisms of sequential media selection, researchers need to embrace the stochasticity and formalize choice behaviors with probabilistic models that specify how previous media selection influences the probability distributions of future selection.

Second, media selection is not a stationary process. People's movie preferences may change over time. They might feel bored after listening to their favorite song on repeat. They may switch between exploring novel news sources and exploiting informative news sources. Thus, researchers must eschew stationarity and properly specify the dynamic mechanisms that govern sequential media selection. Our MDP example demonstrates that people's mental states are non-stationary, contingent on previous media selection, and result in time-varying selection dynamics. Similarly, people's

reward estimates of media options are non-stationary and change through RL or reward generalization processes. People's decision strategies are non-stationary and switch between exploration and exploitation. Each of these theoretical specifications offers a unique way to explain the dynamic and non-stationary nature of sequential media choices. We hope that these recommendations jumpstart a new era of fruitful research investigating sequential media selection.

Data availability

Data availability is not applicable to this article as no new data were created or analyzed in this study.

Funding

No funding was received to assist with the preparation of this article.

Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Notes

1. We recognize that other mechanisms have been proposed and tested. Our ambition is not to exhaustively review all existing mechanisms, as this has already been done (e.g., Hartmann, 2009). Instead, we specify select mechanisms as a theoretical jumping-off point for our main ambition, the computational modeling of sequential media selection.
2. In this equation, the fifth term parameterizes MMT's valence hypothesis (persons in aversive states will prefer hedonically positive stimuli) and the sixth term parameterizes MMT's excitatory homeostasis hypothesis (persons in states of extreme over- or under stimulation will act to return to a baseline).
3. We note that the main goal of this article is to theoretically specify several domain-general mechanisms that govern sequential media selection. Given our focus on content and audience characteristics, we examine the temporal dependencies between previously selected and currently selected media.
4. Both the semantic and temporal dimensions exhibit a time-varying structure. Communication researchers have largely focused on semantic characteristics of media selection. Our efforts in this article focus on the semantic *and* temporal dimensions, which we understand as an additional theoretical contribution.
5. This center dot was intentionally selected to represent the dot product of scalar multiplication. Remember that scalars only quantify magnitude whereas vectors quantify both magnitude and direction.
6. Media channels also change, but less rapidly. Additional theorizing might focus on content distribution channels.
7. Remember that, as shown in Figure 3C, distance can be represented in semantic space.
8. We would like to thank an anonymous reviewer for encouraging us to consider the theoretical generality of value-based decision making and its relationships with other mechanisms of media and medium selection.

References

- Ahn, S. J., Kim, J., & Kim, J. (2022). The bifold triadic relationships framework: a theoretical primer for advertising research in the metaverse. *Journal of Advertising*, 51(5), 592–607.
- Anspach, N. M., & Carlson, T. N. (2020). What to believe? Social media commentary and belief in misinformation. *Political Behavior*, 42(3), 697–718. <https://doi.org/10.1007/s11109-018-9515-z>
- Atkin, C. (1973). Instrumental utilities and information seeking. In P. Clarke (ed.), *New Models for Mass Communication Research* (pp. 307–307). Sage Publications.
- Auer, P., Cesa-Bianchi, N., & Fischer, P. (2002). Finite-time analysis of the multiarmed bandit problem. *Machine Learning*, 47(2), 235–256. <https://doi.org/10.1023/A:1013689704352>
- Bailey, R. L., Liu, J., & Wang, T. (2021a). Primary biological motivators in food advertisements: energy density and sexual appeals compete for appetitive motivational activation. *Communication Research*, 48(3), 379–400. <https://doi.org/10.1177/0093650218793747>
- Bailey, R. L., Wang, T. (Grace), & Liu, J. (2021b). Applying optimal foraging to young adult decision-making after food advertising exposure. *Health Communication*, 36(2), 146–157. <https://doi.org/10.1080/10410236.2019.1669268>
- Bell, D. E., Raiffa, H., & Tversky, A. (1988). *Decision making: descriptive, normative, and prescriptive interactions*. Cambridge University Press.
- Brehmer, B. (1992). Dynamic decision making: human control of complex systems. *Acta Psychologica*, 81(3), 211–241. [https://doi.org/10.1016/0001-6918\(92\)90019-A](https://doi.org/10.1016/0001-6918(92)90019-A)
- Brinberg, M. & Lydon-Staley, D. M. (2023). Conceptualizing and examining change in communication research. *Communication Methods and Measures*, 17(1), 59–82. <https://doi.org/10.1080/19312458.2023.2167197>
- Carpentier, F. R. D. (2020). Mood management. In J. Van den Bulck (ed.), *The International Encyclopedia of Media Psychology* (pp. 1–8). Wiley. <https://doi.org/10.1002/9781119011071.iemp0255>
- Chung, S., & Fink, E. L. (2022). Mathematical models of message discrepancy: previous models and a modified psychological discounting model. *Communication Theory*, 32(4), 471–487. <https://doi.org/10.1093/ct/qtac010>
- Chung, S., Fink, E. L., Waks, L., Meffert, M. F., & Xie, X. (2012). Sequential information integration and belief trajectories: an experimental study using candidate evaluations. *Communication Monographs*, 79(2), 160–180. <https://doi.org/10.1080/03637751.2012.673001>
- Cohen, J. D., McClure, S. M., & Yu, A. J. (2007). Should I stay or should I go? How the human brain manages the trade-off between exploitation and exploration. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, 362(1481), 933–942. <https://doi.org/10.1098/rstb.2007.2098>
- Daft, R. L., & Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. *Management Science*, 32(5), 554–571.
- Davis, J. L., & Chouinard, J. B. (2016). Theorizing affordances: from request to refuse. *Bulletin of Science, Technology & Society*, 36(4), 241–248.
- Daw, N. D., O'Doherty, J. P., Dayan, P., Seymour, B., & Dolan, R. J. (2006). Cortical substrates for exploratory decisions in humans. *Nature*, 441(7095), 876–879. <https://doi.org/10.1038/nature04766>
- Daw, N. D. (2011). Trial-by-trial data analysis using computational models. In M. R. Delgado, E. A. Phelps, & T. W. Robbins (Eds.), *Decision Making, Affect, and Learning: Attention and Performance*, Vol. XXIII. Oxford University Press. <https://doi.org/10.1093/acprof:oso/9780199600434.003.0001>
- Evans, S. K., Pearce, K. E., Vitak, J., & Treem, J. W. (2017). Explicating affordances: a conceptual framework for understanding affordances in communication research. *Journal of Computer-Mediated Communication*, 22(1), 35–52.
- Farrell, S., & Lewandowsky, S. (2018). *Computational modeling of cognition and behavior*. Cambridge University Press.
- Fink, E. L. (1993). Mathematical models for communication: an introduction. *Journal of Communication*, 43(1), 4–7. <https://doi.org/10.1111/j.1460-2466.1993.tb01245.x>
- Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention and Behaviour: An Introduction to Theory and Research*. (Vol. 27). Netherlands: Addison-Wesley Publishing Company.

- Fisher, J. T., & Hamilton, K. A. (2021). Integrating media selection and media effects using decision theory. *Journal of Media Psychology*, 33(4), 215–225. <https://doi.org/10.1027/1864-1105/a000315>
- Fox, J., & McEwan, B. (2017). Distinguishing technologies for social interaction: the perceived social affordances of communication channels scale. *Communication Monographs*, 84(3), 298–318. <https://doi.org/10.1080/03637751.2017.1332418>
- Gittins, J. C. (1979). Bandit processes and dynamic allocation indices. *Journal of the Royal Statistical Society: Series B (Methodological)*, 41(2), 148–164. <https://doi.org/10.1111/j.2517-6161.1979.tb01068.x>
- Goodwin, J. C., Cohen, T., & Rindfleisch, T. (2012). Discovery by scent: discovery browsing system based on the information foraging theory. In *2012 IEEE International Conference on Bioinformatics and Biomedicine Workshops* (pp. 232–239). IEEE. <https://doi.org/10.1109/BIBMW.2012.6470309>
- Gong, X., Huskey, R., Eden, A., & Ulusoy, E. (2023). Computationally modeling mood management theory: a drift-diffusion model of people's preferential choice for valence and arousal in media. *Journal of Communication*, 73(5), 476–493. <https://doi.org/10.1093/joc/jqad020>
- Gong, X., & Huskey, R. (in press). Computational modeling entertainment media choice and decision making in communication science. In N. D. Bowman (Ed.), *DeGruyter handbook of entertainment*. (Vol. 1). DeGruyter.
- Gong, X., & Huskey, R. (2023). Media selection is highly predictable, In principle. *Computational Communication Research*, 5(1), 1–32. <https://doi.org/10.5117/CCR2023.1.15.GONG>
- Gong, X., Huskey, R. (2022, May). *Modeling human music mobility*. Paper presented at 72nd annual conference of the international communication association, Paris, France.
- Guest, O., & Martin, A. E. (2021). How computational modeling can force theory building in psychological science. *Perspectives on Psychological Science*, 16(4), 1–14. <https://doi.org/10.1177/1745691620970585>
- Hartmann, T. (2009). *Media choice: a theoretical and empirical overview*. Routledge.
- Hofman Jake M. Watts Duncan J. Athey Susan. Garip Filiz. Griffiths Thomas L. Kleinberg Jon. Margetts Helen. Mullainathan Sendhil. Salganik Matthew J. Vazire Simine. Vespignani Alessandro. Yarkoni Tal. Integrating explanation and prediction in computational social science. *Nature*. 595 (7866) 2021. 181–188. Jul 2021. <https://doi.org/10.1038/s41586-021-03659-0>. 34194044.
- Huskey, R., Bue, A. C., Eden, A., Grall, C., Meshi, D., Prena, K., Schmalzle, R., Scholz, C., Turner, B. O., & Wilcox, S. (2020). Marr's tri-level framework integrates biological explanation across communication subfields. *Journal of Communication*, 70(3), 356–378. <https://doi.org/10.1093/joc/jqaa007>
- Jaiswal, A. K., Tiwari, P., & Hossain, M. S. (2020). Predicting users' behavior using mouse movement information: an information foraging theory perspective. *Neural Computing and Applications*, 35(5), 23767–23780. <https://doi.org/10.1007/s00521-020-05306-7>
- Jensen, K. B., & Rosengren, K. E. (1990). Five traditions in search of the audience. *European Journal of Communication*, 5(2), 207–238. <https://doi.org/10.1177/0267323190005002005>
- Katz, E., Haas, H., & Gurevitch, M. (1973). On the use of the mass media for important things. *American Sociological Review*, 38(2), 164–181. <https://doi.org/10.2307/2094393>
- Keene, J. R., & Lang, A. (2016). Dynamic motivated processing of emotional trajectories in public service announcements. *Communication Monographs*, 83(4), 468–485. <https://doi.org/10.1080/03637751.2016.1198040>
- Knobloch-Westerwick, S. (2014). *Choice and preference in media use: advances in selective exposure theory and research*. Routledge.
- Knobloch-Westerwick, S., Carpentier, F. D., Blumhoff, A., & Nickel, N. (2005). Selective exposure effects for positive and negative news: testing the robustness of the informational utility model. *Journalism & Mass Communication Quarterly*, 82(1), 181.
- Levy, D. J., & Glimcher, P. W. (2012). The root of all value: a neural common currency for choice. *Current Opinion in Neurobiology*, 22(6), 1027–1038. <https://doi.org/10.1016/j.conb.2012.06.001>
- Li, L., Chu, W., Langford, J., & Schapire, R. E. (2010, April). A contextual-bandit approach to personalized news article recommendation. In *Proceedings of the 19th International Conference on World Wide Web* (pp. 661–670). Association for Computing Machinery. <https://doi.org/10.1145/1772690.1772758>
- Liang, Y., & Willemsen, M. C. (2021, September). The role of preference consistency, defaults and musical expertise in users' exploration behavior in a genre exploration recommender. In *Proceedings of the 15th ACM Conference on Recommender Systems* (pp. 230–240). Association for Computing Machinery. <https://doi.org/10.1145/3460231.3474253>
- Lindström, B., Bellander, M., Schultner, D. T., Chang, A., Tobler, P. N., & Amodio, D. M. (2021). A computational reward learning account of social media engagement. *Nature Communications*, 12(1), 1311. <https://doi.org/10.1038/s41467-020-19607-x>
- Liu, H., Mulholland, P., Song, D., Uren, V., & Rüger, S. (2010). Applying information foraging theory to understand user interaction with content-based image retrieval. In *Proceedings of the third symposium on information interaction in context* (pp. 135–144). Association for Computing Machinery. <https://doi.org/10.1145/1840784.1840805>
- Lydon-Staley, D. M., Zhou, D., Blevins, A. S., Zurn, P., & Bassett, D. S. (2020). Hunters, busybodies and the knowledge network building associated with deprivation curiosity. *Nature Human Behaviour*, 5(3), 327–336. <https://doi.org/10.1038/s41562-020-00985-7>
- McQuail, D. (1997). *Audience analysis*. Sage Publications.
- Mnih, V., Kavukcuoglu, K., Silver, D., Graves, A., Antonoglou, I., Wierstra, D., & Riedmiller, M. (2013). Playing Atari with deep reinforcement learning. ArXiv:1312.5602 [Cs]. <http://arxiv.org/abs/1312.5602>
- Nabi, R. L., & Green, M. C. (2015). The role of a narrative's emotional flow in promoting persuasive outcomes. *Media Psychology*, 18(2), 137–162. <https://doi.org/10.1080/15213269.2014.912585>
- Nabi, R. L., & Oliver, M. B. (2009). *The SAGE handbook of media processes and effects*. SAGE.
- Nabi, R. (2020). Media and emotion. In M. B. Oliver, A. Raney, & J. Bryant (Eds.), *Media effects: advances in theory and research* (4th ed., pp. 163–178). Routledge.
- Niv, Y. (2009). Reinforcement learning in the brain. *Journal of Mathematical Psychology*, 53(3), 139–154. <https://doi.org/10.1016/j.jmp.2008.12.005>
- Ostic, D., Qalati, S. A., Barbosa, B., Shah, S. M. M., Galvan Vela, E., Herzallah, A. M., & Liu, F. (2021). Effects of social media use on psychological well-being: a mediated model. *Frontiers in Psychology*, 12, 678766. <https://www.frontiersin.org/article/10.3389/fpsyg.2021.678766>
- Perse, E. M., & Lambe, J. (2016). *Media effects and society* (2nd ed.). Routledge. <https://doi.org/10.4324/9780203854693>
- Pirolli, P. (2007). *Information foraging theory: adaptive interaction with information*. Oxford University Press.
- Pirolli, P., & Card, S. (1995). Information foraging in information access environments. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 51–58). Association for Computing Machinery. <https://doi.org/10.1145/223904.223911>
- Pyke, G. H. (1984). Optimal foraging theory: a critical review. *Annual Review of Ecology and Systematics*, 15(1), 523–575. <https://doi.org/10.1146/annurev.es.15.110184.002515>
- Rangel, A., Camerer, C., & Montague, P. R. (2008). A framework for studying the neurobiology of value-based decision making. *Nature Reviews Neuroscience*, 9(7), 545–556. <https://doi.org/10.1038/nrn2357>
- Ratcliff, R., & McKoon, G. (2007). The diffusion decision model: theory and data for two-choice decision tasks. *Neural Computation*, 20(4), 873–922. <https://doi.org/10.1162/neco.2008.12-06-420>
- Reinecke, L., Tamborini, R., Grizzard, M., Lewis, R., Eden, A., & David Bowman, N. (2012). Characterizing mood management as

- need satisfaction: the effects of intrinsic needs on selective exposure and mood repair. *Journal of Communication*, 62(3), 437–453. <https://doi.org/10.1111/j.1460-2466.2012.01649.x>
- Roberts, I. D., & Hutcherson, C. A. (2019). Affect and decision making: insights and predictions from computational models. *Trends in Cognitive Sciences*, 23(7), 602–614. <https://doi.org/10.1016/j.tics.2019.04.005>
- Ruggiero, T. E. (2000). Uses and gratifications theory in the 21st century. *Mass Communication and Society*, 3(1), 3–37. https://doi.org/10.1207/S15327825MCS0301_02
- Schmälzle Ralf. Theory and Method for Studying How Media Messages Prompt Shared Brain Responses Along the Sensation-to-Cognition Continuum. *Communication Theory*. 2022. 32 (4) 450–460. Oct 2022. [10.1093/ct/qtac009](https://doi.org/10.1093/ct/qtac009).
- Schmälzle, R., & Huskey, R. (2023). Integrating media content analysis, reception analysis, and media effects studies. *Frontiers in Neuroscience*, 17, 1155750. <https://doi.org/10.3389/fnins.2023.1155750>
- Schramm, W. (1955). Information theory and mass communication. *Journalism Quarterly*, 32(2), 131–146. <https://doi.org/10.1177/107769905503200201>
- Schulz, E., Bhui, R., Love, B. C., Brier, B., Todd, M. T., & Gershman, S. J. (2019). Structured, uncertainty-driven exploration in real-world consumer choice. *Proceedings of the National Academy of Sciences of the United States of America*, 116(28), 13903–13908. <https://doi.org/10.1073/pnas.1821028116>
- Sears, D. O., & Freedman, J. L. (1967). Selective exposure to information: a critical review. *The Public Opinion Quarterly*, 31(2), 194–213.
- Shade, D. D., Kornfield, S., & Oliver, M. B. (2015). The uses and gratifications of media migration: investigating the activities, motivations, and predictors of migration behaviors originating in entertainment television. *Journal of Broadcasting & Electronic Media*, 59(2), 318–341. <https://doi.org/10.1080/08838151.2015.1029121>
- Smaldino, P. E. (2017). Models are stupid, and we need more of them. In R. R. Vallacher, S. J. Read, A. Nowak (Eds.), *Computational Social Psychology* (pp. 311–331). Routledge.
- Smaldino, P. E. (2020). How to translate a verbal theory into a formal model. *Social Psychology*, 51(4), 207–218. <https://doi.org/10.1027/1864-9335/a000425>
- Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: an introduction* (2nd ed.). A Bradford Book.
- Tesauro, G. (1992). Practical issues in temporal difference learning. *Machine Learning*, 8(3), 257–277. <https://doi.org/10.1007/BF00992697>
- Tkalcic, M., & Chen, L. (2015). Personality and recommender systems. In *Recommender systems handbook* (pp. 715–739). Boston, MA: Springer US.
- Tria, F., Loreto, V., Servedio, V. D. P., & Strogatz, S. H. (2014). The dynamics of correlated novelties. *Scientific Reports*, 4(1), Article 1. <https://doi.org/10.1038/srep05890>
- Vandekerckhove, J., Matzke, D., & Wagenmakers, E.-J. (2015). Model comparison and the principle of parsimony. In J. R. Busemeyer, Z. Wang, J. T. Townsend, & A. Eidels (Eds.), *The Oxford handbook of computational and mathematical psychology* (pp. 300–319). Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780199957996.013.14>
- van Rooij, I., & Baggio, G. (2021). Theory before the test: how to build high-verisimilitude explanatory theories in psychological science. *Perspectives on Psychological Science*, 16(4), 682–697. <https://doi.org/10.1177/1745691620970604>
- Veenstra, A. S., Hossain, M. D., & Lyons, B. A. (2014). Partisan media and discussion as enhancers of the belief gap. *Mass Communication and Society*, 17(6), 874–897. <https://doi.org/10.1080/15205436.2013.855791>
- Vermeer Susan. Trilling Damian. Toward a Better Understanding of News User Journeys: A Markov Chain Approach. *Journalism Studies*. 2020. 21 (7) 879–894. May 2020. [10.1080/1461670X.2020.1722958](https://doi.org/10.1080/1461670X.2020.1722958).
- Wang, X., Wang, Y., Hsu, D., & Wang, Y. (2014). Exploration in interactive personalized music recommendation: a reinforcement learning approach. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, 11(1), 1–22.
- Wang, T. G., & Bailey, R. L. (2023). Does sequence matter? An investigation into the motivated processing of sequentially coactive messages. *Journal of Media Psychology: Theories, Methods, and Applications*, 35(2), 120–129. <https://doi.org/10.1027/1864-1105/a000353>
- Wang, Z. (2014). Bridging media processing and selective exposure: a dynamic motivational model of media choices and choice response time. *Communication Research*, 41(8), 1064–1087. <https://doi.org/10.1177/0093650214534963>
- Wang, Z., Busemeyer, J. R., & Lang, A. (2006). Grazing or staying tuned: a stochastic dynamic model of channel changing behavior. In *Proceedings of the Twenty-eighth Annual Conference of the Cognitive Science Society* (pp. 870–875). Cognitive Science Society.
- Wang, Z., Lang, A., & Busemeyer, J. R. (2011). Motivational processing and choice behavior during television viewing: an integrative dynamic approach. *Journal of Communication*, 61(1), 71–93. <https://doi.org/10.1111/j.1460-2466.2010.01527.x>
- Watkins, C. (1989). *Learning from delayed rewards* [Doctoral thesis, King's College]. http://www.cs.rhul.ac.uk/~chrisw/new_thesis.pdf
- Watkins, C. J. C. H., & Dayan, P. (1992). Q-learning. *Machine Learning*, 8(3), 279–292. <https://doi.org/10.1007/BF00992698>
- Weber, R., Eden, A., Huskey, R., Mangus, J. M., & Falk, E. B. (2015). Bridging media psychology and cognitive neuroscience: challenges and opportunities. *Journal of Media Psychology*, 27(3), 146–156. <https://doi.org/10.1027/1864-1105/a000163>
- Wiradhany, W., Baumgartner, S., & de Bruin, A. (2021). Exploitation–exploration model of media multitasking. *Journal of Media Psychology: Theories, Methods, and Applications*, 33(4), 169–180. <https://doi.org/10.1027/1864-1105/a000303>
- Wilson, R. C., & Collins, A. G. (2019). Ten simple rules for the computational modeling of behavioral data. *Elife*, 8, e49547. <https://doi.org/10.7554/eLife.49547>
- Wu, C. M., Schulz, E., Speekenbrink, M., Nelson, J. D., & Meder, B. (2018). Generalization guides human exploration in vast decision spaces. *Nature Human Behaviour*, 2(12), 915–924. <https://doi.org/10.1038/s41562-018-0467-4>
- Xu, S., Wang, Z. (Joyce), & David, P. (2016). Media multitasking and well-being of university students. *Computers in Human Behavior*, 55, 242–250. <https://doi.org/10.1016/j.chb.2015.08.040>
- Yarkoni Tal. Westfall Jacob. Choosing Prediction Over Explanation in Psychology: Lessons From Machine Learning. *Perspectives on psychological science : a journal of the Association for Psychological Science*. 12 (6) 2017. 1100–1122. Nov 2017. [10.1177/1745691617693393](https://doi.org/10.1177/1745691617693393). 28841086.
- Zhang, S., Yao, L., Sun, A., & Tay, Y. (2019). Deep learning based recommender system: a survey and new perspectives. *ACM Computing Surveys (CSUR)*, 52(1), 1–38.
- Zillmann, D. (2000). Mood management in the context of selective exposure theory. *Annals of the International Communication Association*, 23(1), 103–123. <https://doi.org/10.1080/23808985.2000.11678971>
- Zillmann, D., & Bryant, J. (2013). *Selective exposure to communication*. Routledge.