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Bridging Media Processing and Selective Exposure: A Dynamic Motivational Model of Media Choices and Choice Response Time

Zheng Wang[1]

Abstract

Based on the dynamic motivational activation (DMA) theoretical framework, a dynamic and stochastic semi-Markov choice model of channel changing behavior, called the ChaCha model, is developed and submitted to empirical testing. The ChaCha model integrates the motivated media processing and selective exposure behavior, and formalizes their reciprocal, recursive dynamic influences. It incorporates a logistic type of ratio of strength choice model, a reinforcement learning model, and the diffusion model of choice time to simultaneously predict sequential media channel choices and channel viewing durations. Real-time channel choice data from a selective exposure TV viewing experiment are used to test the model and to illustrate how this model can be used to understand dynamic cognitive mechanisms underlying the observed media choice behavior.

Keywords

dynamic, motivation, media choice, choice response time, reinforcement learning, diffusion, selective exposure

A typical 8- to 18-year-old in the United States is surrounded by "3.8 TVs, 2.8 DVD or VCR players, 1 digital video recorder, 2.2 CD players, 2.5 radios, 2 computers, and 2.3 console video game players" at home and spends almost a workday (7 hours 38 minutes) using media every day—an increase of 1 hour and 17 minutes from 2004

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(Rideout, Foehr, & Roberts, 2010, pp. 6-9). In an increasingly media-saturated society, such as the United States, rocketing media options and accessibility make it critical to understand the dynamics of media choice behavior over time. How do we interact with and adapt to the lavish, continuously changing media landscape? What are the fundamental cognitive mechanisms shaping varying behaviors of media use? Questions like these are pursuit by both media scholars and practitioners.

On the one hand, two areas of scholarly research have accumulated valuable understanding to these questions. One has focused on how selective exposure to media is affected by various media and audience factors such as violent content and personal traits (e.g., Kim, 2007; Knobloch-Westerwick & Hastall, 2010; Slater, Henry, Swaim, & Anderson, 2003). The other has examined the real-time processing of media and identified the roles of specific media features, such as production techniques, in eliciting and altering attention and emotion (e.g., Lang, 2006; Potter & Choi, 2006). A primary goal of the current study is to start theoretically bridging selective exposure and media processing research based on the theoretical framework of dynamic motivational activation (DMA; Wang, Lang, & Busemeyer, 2011; Wang, Solloway, Tchernev, & Barker, 2012; Wang & Tchernev, 2012). To capture and test the complex, dynamic, and reciprocal influences between media selective exposure and media information processing over time, a specific formal (i.e., mathematical or computational) cognitive model is developed based on DMA.

On the other hand, although new measures and metrics have been developed with the evolution of media technologies, the most popular and important audience measures used by media and marking research industry, such as ratings, shares, and cumulative audience estimates, focus on two behavioral variables—media choices (e.g., TV channels viewed, websites browsed) and time spent on the choices (often called choice response time in decision science, for example, viewing and browsing durations). Typical media industry research tends to be descriptive and aggregative for its practical reasons, and thus does not focus on understanding the mechanisms and processes underlying the observed behavioral data. Hence, the other primary goal of this study is to start bridging our scholarly understanding of media processing and selection to the two behavioral variables of crucial importance to the industry. Specifically, the study proposes a single cognitive choice model that simultaneously explains and predicts media channel choices and choice response time. A large body of choice behavior research in decision science has pointed out that choice probability and choice response time are inherently connected to each other in producing choice behavior (Busemeyer & Townsend, 1993; Laming, 1968; Luce, 1986). Analyzing them separately overlooks intrinsic dynamics of choice behavior and leads to misleading findings, and therefore choice models should aim for predicting both choice probability and response time using a single mechanism (Busemeyer & Diederich, 2010; Diederich, 1997; Luce, 1986). This study is among the first attempts to achieve this in media choice research. As an initial step in developing a formal theoretical model, a selective exposure TV viewing laboratory experiment is used to illustrate and test the proposed model.

Reciprocal, Recursive Influences of Motivated Media Processing and Media Choice

A large range of factors related to both the audience and the media tangle together, making it difficult to identify specific processes leading to media choice behavior. A formal mathematical or computational cognitive model can help disentangle these processes to better understand underlying cognitive mechanisms, which is hard to achieve by verbal formulations of theories alone (Blalock, 1969; Busemeyer & Diederich, 2010; McPhee & Poole, 1982).[1] Based on the DMA theoretical framework, a computational model is proposed to specify the cognitive mechanisms involved in media processing and choice behavior.

The DMA aims to explain the dynamics during media processing, media choices, and their reciprocal, recursive influences over time (Wang et al., 2011; Wang, Morey, & Srivastava, 2010, 2014; Wang & Tchernev, 2012). Based on motivated media processing theory (Lang, 2006) and motivated decision theory (Busemeyer, Townsend, & Stout, 2001), the DMA theorizes media use as a complex dynamic process: Continuously changing media content serves as motivational inputs to the information processing system of the media user, and the system's self-generating and self-organizing properties moderate the influences from the media inputs to generate dynamic affective, cognitive, and behavioral responses across time. The media user's responses at any time point are determined not only by the media input at that time point but also by his or her previous responses.

Previous work along the line of the DMA has formally tested the time-dependent, dynamic nature of attentional and affective responses during the real-time processing of entertainment media (Wang et al., 2011) and persuasive messages (Wang & Lang, 2012; Wang, Morey et al., 2010, 2014; Wang, Solloway et al., 2012), as well as longitudinal choice behavior of media multitasking and social media (Wang & Tchernev, 2012; Wang, Tchernev et al., 2012). Specifically, using longitudinal experience sampling method, Wang and Tchernev (2012) have tested the reciprocal causality between media choice behavior and media use motivations in everyday lives of college students. The study shows that students select to engage in media multitasking when they are motivated by multiple needs at the time. Some of the needs are—and some are not—gratified by the media-multitasking activity, which further determines subsequent media use and choices.

Using real-time experimental data, the current study will further test the reciprocal influences of media processing and media choice behavior, with a focus on specifying cognitive and decision mechanisms underlying both media choice and choice time dynamics. With this theoretical focus, the proposed model can be adopted to a large variety of media choice and use contexts, such as website browsing, social media activities, news selective exposure, and selections of an assortment of media—in both naturalistic and manipulated experimental contexts. In the current study, the model is illustrated using a TV channel changing context and, accordingly, specified to examine the phenomenon. The model integrates well-established cognitive mechanisms of motivated choice, reinforcement learning, and the diffusion process of choice response time into a single mechanism to simultaneously explain and predict both the probability of channel changes and viewing durations between changes. This model serves as a primary example of formalizing the DMA theoretical framework to predict dynamic, interacting, motivated media processing and choice behavior in a specific communication context.

TV Channel Changing Behavior

Why study TV channel changing behavior? Although personal and portable video technologies become increasingly popular, TV still is the primary form of video media for most Americans. According to Nielson data of the United States in 2010, the TV audience is more than 14 times larger than the mobile video audience (Gahran, 2010). In fact, traditional TV audience has grown over the years (Nielsen, 2013). According to the most recent data, on average, an American spent 157:32 (hours:minutes) watching traditional TV in a month; in comparison, monthly time spent on time-shifted TV is 13:23, on DVD/Blue Ray device is 5:56, on the Internet via a computer is 28:28, on video on Internet is 8:20, and on video on a mobile phone is 5:29 (Nielsen, 2013). In addition, total expenditure on TV ads increased in 2013 compared with previous years (TVB, 2013). Channel changing has long been recognized as one of the largest obstacles that TV professionals and marketers have to overcome to entice and seize audiences (Ferguson & Eastman, 2006). Thus, a good theoretical understanding of TV viewers' channel changing behavior can be helpful to marketing—including pro-social marketing—researchers. Before presenting the formal model, it is necessary to briefly review our current conceptual understanding of channel changing behavior.

Both Media Features and Audience's Characteristics Affect Channel Changing

Media use is theorized as interactions between individuals and media (e.g., Lang, 2006; Wang et al., 2011). Both media features and an viewer's characteristics can influence whether the viewer decides to stay or graze. A wealth of research has shown that the TV program format (e.g., pacing and story length), content (e.g., emotion and genres), and context (e.g., air time and alternative channels) can affect channel changing behavior. For instance, viewers are more likely attracted to media messages that are shorter and faster (Bellamy & Walker, 1996; Eastman & Newton, 1995) or with more cutting and short scenes (Eastman & Neal-Lunsford, 1993). Also, channel changing patterns are impacted by story length and production pacing (Lang et al., 2005) as well as sensational content and tabloid style presentation features (Fox, Park, Grabe, & Lee, 2005). Individual differences play a role in channel changing behaviors as well. For example, younger viewers are found to change channels more frequently than older viewers (Eastman & Newton, 1995) and their viewing pattern is more easily affected by media format features than older viewers who respond more to content (Lang et al., 2005). However, it is unclear yet what are the specific cognitive mechanisms driving these observed behavioral patterns. This study proposes a formal cognitive model to start to specify and test the underlying mechanisms.

Increased Boredom Leads to Channel Changing

It has been debated whether channel changing is an active or a passive behavior (Ferguson & Perse, 1993). One view argues that frequent channel changing indicates the user is active, who constantly evaluates the media content and makes selections based on personal motivations and goals (e.g., Eastman & Newton 1995). The other view suggests that channel changing is resulted from detached, low-involvement viewing, and lower levels of attention (e.g., Perse, 1990, 1998). Recently, based on the limited capacity theory of media processing, Lang et al. (2005) suggested that active viewers would show a consistently high level of attentional effort and arousal while viewing TV. However, if people view passively, their attentional effort and arousal levels would decrease over time that leads to changing channels; and upon the change, attentional effort and arousal should increase as the viewer orients to the new content. Using real-time psychophysiological measures to study viewers' levels of attentional effort and arousal, and using recognition to measure information encoding, the authors found evidence that supports the passive viewing rather than the active viewing perspective. This study will further formally specify and test the active versus passive viewing hypothesis.

A Dynamic Stochastic Model of Media Channel Choices and Choice Response Time

The proposed model is named ChaCha—after the first three letters of "channel" and "changing." In a general sense, "channel" can refer to any information channel, such as different TV channels, websites, news media, and various traditional or new video content devices (traditional TV, DVDs, tablets, mobile phones). ChaCha is formulated using a semi-Markov model (Bhattacharya & Waymire, 1990; Cox & Miller, 1965), which conceives of different channels as states of the Markov chain and of switching between channels as transitions between states.[2] A strength of the semi-Markov model is that it predicts not only the choice probabilities of the states but also the distribution of time between the transitions (Böckenholt, 2005). This flexibility enables us to model channel changing behavior where time durations between channel switches vary extensively and is an essential measure associated with channel choices. In particular, based on the DMA theoretical framework (Wang et al., 2011; Wang & Tchernev, 2012), the ChaCha model formalizes a viewer's choice of media channels as being determined by motivational values associated with the channel options. Importantly, the motivational values for the media channel choices are not static. Instead, they fluctuate depending on the dynamic changes in the mediated environment introduced by media choices and use (Busemeyer et al., 2001; Slater, 2007; Wang & Tchernev, 2012; Wang, Tchernev et al., 2012). Specifically in ChaCha, the motivational values associated with media channel options are continuously updated through a reinforcement learning process, which is, in turn, determined by the choice behavior. In summary, ChaCha formalizes several interconnected dynamic cognitive mechanisms underlying the media choice behavior (in this example, the TV channel changing behavior) to

Table 1. A Sample of Channel Choice and Choice Response Time (i.e., Viewing Duration) Data.

Channel	Time
C_0	t_0
C_1	t_1
. . .	. . .
C_k	t_k
C_{k+1}	t_{k+1}
. . .	. . .
C_n	t_n

capture the dynamic reciprocal influences of media processing and choice behavior, and to predict the media choice probability and media use duration for a given media option. Details follow.

Media Channel Choices are Determined by Motivational Values

A sample of typical media channel choice data is illustrated in Table 1. The left column lists media channels that a viewer sequentially watched and the right column shows the viewing duration of each channel, that is, the duration of watching a channel before switching to another. The probability of choosing any "new" channel during a switch is proposed to be determined by a logistic type of ratio of strength model, which has been commonly used to explain choice behavior (e.g., Hosmer & Lemeshow, 2000). The logistic model of probabilities of choosing any "new" channel is defined as the following.

First, each channel has a *motivational value*, which determines how likely people will select a channel at each switch, and if selected, how long people will stay on the channel. This is based on motivated cognition and decision literature (e.g., Busemeyer et al., 2001) as well as media selective exposure literature (e.g., Slater, 2007) as incorporated and formally tested in the DMA theoretical framework (e.g., Wang et al., 2011; Wang & Tchernev, 2012; Wang, Tchernev et al., 2012). As previously reviewed, the motivational value can be affected by both media channel variables, such as emotional content and production features, as well as audience variables, such as age and the appetitive-aversive motivational reactivity trait (e.g., Lang et al., 2005; Wang et al., 2011). The ChaCha model defines $x_j(k)$ as the motivational value of channel j at the kth switch (i.e., row k in Table 1), which is the motivational value used to predict the kth switch after viewing all the previous $k - 1$ channels.

Then, we transform the motivational values by exponential transformation (see Chapter 5 of Busemeyer & Diederich, 2010). This is because the logistic model uses a ratio of strengths of the alternative options to compute choice probabilities, and the strengths of options must be positive so that the ratio is a probability, which ranges from 0 (certainly not chosen) to 1 (certainly chosen). Thus, channel motivational values, which can range from negative (aversive motivational) to positive (appetitive motivational), are transformed by exponential transformation, $v_j(k) = \exp[x_j(k)]$. The transformed motivational value is called *motivational strength*, and it ranges from 0 to infinity. As described below, the ratio between the motivational strength of a channel versus those of all available options ranges from 0 to 1.

Based on the channel motivational strengths, the probability of selecting a channel can be computed. If a viewer is watching channel i before the kth switch (denoted $C_{k-1} = i$) and decides to switch, the viewer must switch to a channel other than i. Then, the probability of choosing channel j among all the potential choices for the kth switch is

$$P_k = P[C_k = j \mid C_{k-1} = i] = \frac{v_j(k)}{\sum_{l \neq i} v_l(k)}. \tag{1}$$

Here, P_k is a conditional probability: The probability of choosing channel j on the kth switch, given that channel i is viewed right before this switch. The numerator is the motivational strength of channel j, and the denominator is the sum of motivational strengths of all channels except for the currently viewed channel i. In other words, the probability of choosing a "new" channel depends on how large its motivational strength is compared with the total strengths of all potential channel options. Then, how are the motivational strengths for channels determined and how do they evolve during the viewing experience?

Motivational Values Change Through Reinforcement Learning

The DMA theoretical framework emphasizes that media motivational values (to media users), which determine the media users' media choices, are reciprocally affected by the choices (Wang et al., 2011; Wang & Tchernev, 2012; Wang, Tchernev et al., 2012). It is through this reciprocal causality that we adaptively interact with our mediated environments. In the TV viewing environment examined here, new information is learned through watching different channels, which changes motivational values associated with the channels and consequently determines which channel to view. This process can be viewed as learning from experience. In ChaCha, it is formalized using the most established learning model in cognitive science, reinforcement learning (Busemeyer & Myung, 1992; Erev & Roth, 1998).

Reinforcement learning is learning through interacting with the environment without supervising rules. In a typical reinforcement learning model, an agent perceives inputs from the environment and accordingly chooses an action; in turn, the action output changes the state of the environment, which consequently changes the environment inputs to the agent. The agent evaluates the changes as rewards or punishments. It is through this trial and error process over time that the agent learns how to choose actions to increase the total rewards in the long run. This process differs from another popular learning model—supervised learning, where available choices and input-output pairs are explicitly defined as correct or incorrect to guide the agent's actions. It is reasonable to theorize media consumption as an unsupervised reinforcement learning process, at least in most TV viewing contexts. In most cases, watching TV is unlikely, as theorized by supervised learning models, to be guided by explicit top-down rules such as "You have channels A, B, C, D, E, F, and G" and "Channel A is the correct choice," and you are given this type of instructions each moment in time. Instead, previous research (e.g., Lang et al., 2005; Perse, 1990, 1998; Wang et al., 2011; Wang & Tchernev, 2012) suggests that media use is characterized by bottom-up experience (e.g., being stimulated by the content and format of programs) and evaluation of the mediated environment (e.g., individuals' processing of the programs). Adaptive behaviors (e.g., changing channels), in turn, can change the mediated environment based on individuals' evaluations (Wang & Tchernev, 2012; Wang, Tchernev et al., 2012).

Both media content and format can influence the motivational value associated with each channel, and thus can shape the reinforcement learning process that is used to update the motivational values. Specifically, the example shown here tests the effects of two media format features—production pacing (fast vs. slow) and length of news stories (long vs. short). Both features relate to the sensation values of media. Research has found that individuals seek different activities, such as more or less sensational media activities, to maintain their preferred stimulation levels (e.g., Stephenson & Southwell, 2006). Pacing and story length are recognized as important news programming variables that interact with each other to affect attention, emotion, and selective exposure to the media content (e.g., Lang et al., 2005). Thus, in the ChaCha model, it is expected that pacing and story length have an interaction effect on the reinforcement learning process (*Hypothesis 1*). More specifically, the reinforcement learning process is formalized as the following. On the one hand, if channel i is watched before the kth switch, this viewing experience produces a change in the motivational value of the watched channel:

$$x_i(k) = x_i(k-1) + D_1\beta_1 + D_2\beta_2 + D_1D_2\beta_3, \tag{2}$$

where β_1, β_2, and β_3 are the changes of motivational value of channel i produced by the channel features. In our case, pacing and story length are included and dummy coded by D_1 (1 = fast pacing, 0 = slow pacing) and D_2 (1 = long stories, 0 = short stories). The model terms, $D_1\beta_1$ and $D_2\beta_2$, are the main effects of the two features, and the product $D_1D_2\beta_3$ is their interaction effect.

On the other hand, not being viewed may produce an expected motivational value on unselected channels. Because of humans' needs and curiosity to explore new information (Kashdan, Rose, & Fincham, 2004; Litman, 2005), the expected motivational value may be positive/appetitive and lead to an increase in the motivational value of the unselected channel. It is also possible that because lower attention weight on an option makes it less important or appetitive (Busemeyer & Townsend, 1993; Milosavljevic, Navalpakkam, Koch, & Rangel, 2012), the expected motivational value may be negative/aversive, leading to a decrease of the motivational value of the unselected channel. Hence, not being watched is hypothesized to produce an expected motivational value, which is a change on a channel's existing motivational value

(*Hypothesis 2*). That is, if channel j is not watched before the kth switch, its motivational value does not remain static but will change by α, the expected motivational value that is typically called the learning rate parameter in reinforcement learning models:

$$x_j(k) = x_j(k-1) + \alpha \tag{3}$$

Thus far, we have specified how channel choice probabilities are determined by continuously updated channel motivational values, which, in turn, are affected in real-time by channel choices and what is being viewed. Then, when does a viewer decide to change channels?

Motivational Decay and Viewing Durations

Previous research has contributed channel switches to motivational decay. Perse (1990) found that channel changing behavior is negatively correlated with self-reported attention and elaboration, and channel changing starts "because interest in what is on the channel wanes" (p. 220). This understanding is supported by real-time attentional responses as indicated by physiological data during TV viewing (Lang et al., 2005). According to the DMA, media information activates media users' motivation that subsequently drives attention to the information (Lang, 2006; Wang et al., 2011; Wang, Solloway et al., 2012); the decay in motivation leads to the decay in attention and excitement to the content, which causes the media user to switch from the channel (Lang et al., 2005; Wang & Lang, 2012). This decay process of motivation determines how much time spent on a channel before the viewer switches to another.

Although rarely rigorously studied in the field of communication yet, response time has long been recognized as a primary measure associated with choice behavior and is essential for revealing underlying cognitive processes underlying decision and choice behavior (Laming, 1968; Luce, 1986). Communication and marketing practitioners also argue for the importance of understanding both media choices and time spent on each choice (e.g., Klaassen, 2009). In ChaCha, response time is the duration of media use before the individual decides to switch to another media or channel. Cognitive scientists often use a diffusion model (Luce, 1986) to model response time in decision and choice behavior (e.g., Busemeyer & Johnson, 2004; Busemeyer & Townsend, 1993; Ratcliff & Rouder, 1998). Simply put, a choice is not made instantly, but instead, it is based on sequential sampling of cumulative evidence for selecting an option over the others. When the cumulative evidence reaches a certain threshold, a choice is made. A diffusion model formalizes this sequential sampling and cumulative-to-threshold processes. In the TV viewing context, the viewer begins with some initial motivational strength in a channel. The motivational strength fluctuates during the viewing of the channel, but in general, it decays and the tendency to change channels increases across time (Lang et al., 2005; Perse, 1990). The amount of motivation decay and the tendency to change accumulates stochastically across time until it reaches a threshold, at which point the viewer decides to switch. The threshold varies across individuals with different tolerance for motivational decay (i.e., lack of interest, boredom). The probability of a channel being selected at this switch is estimated using the ratio of strength choice model as explained earlier. Thus, coherently integrating the ratio of strength choice model and the diffusion model, ChaCha connects choice probability and choice response time, and predicts them simultaneously. This differs from the approach that analyzes choice data and choice time data separately. The latter loses the theoretical connection and restriction on the two interdependent variables of choice behavior and may generate misleading understanding of the underlying cognitive mechanisms (Busemeyer & Townsend, 1993; Laming, 1968; Luce, 1986; Ratcliff & Rouder, 1998).

In ChaCha, the decay process of motivation is stochastic (i.e., non-deterministic) because media content, such as TV programs examined here, continuously involves variations of content and production elements, such as changes of emotional scenes, personal relevance, music, and production effects (e.g., Potter & Choi, 2006). These changes continuously and stochastically update channel motivational values and strengths. Thus, the decay process and the tendency to change channels are also stochastic. However, the mean rate of the decay for the current channel and the tendency to change to a new channel is inversely related to the motivational strength of the current channel, as explained next.

Suppose that the *i*th channel is being viewed and it has strength v_i. Define time t as the viewing duration on a channel and let $M(t)$ represent cumulative motivation decay (i.e., the tendency to change) after time t. Let h represent a small unit of time. Then, according to the discrete time version of the diffusion model, called the random walk model (Laming, 1968; Link & Heath, 1975; Luce, 1986),

$$M(t+h) = M(t) + h \cdot v_i^{-1} + \varepsilon(t+h), \tag{4}$$

where $\varepsilon(t + h)$ is an independent noise term with a variance equal to $h\sigma^2$. The random walk process continues to drift until the cumulative motivation to change crosses a threshold θ. The process stops as soon as the threshold is reached and then the channel is changed. Figure 1 illustrates this process for two channels.

If the small time step h approaches zero to produce a continuous time diffusion process, then the distribution of stopping times or the viewing durations are a Wald distribution, with its probability density function being defined as a function of time duration t:

$$f(t) = \left(\frac{\lambda}{2\pi t^3}\right)^{\frac{1}{2}} \exp\left[-\frac{\lambda}{2\mu^2 t}(t-\mu)^2\right], \tag{5}$$

where $\mu = \theta / v_i^{-1} = v_i \cdot \theta$ is the mean of the stopping time distribution and $\lambda = (\theta/\sigma)^2$, which determines the shape of the distribution (Luce, 1986, p. 509). Therefore, the ChaCha model formalizes channel choices response time (i.e., viewing durations) as a

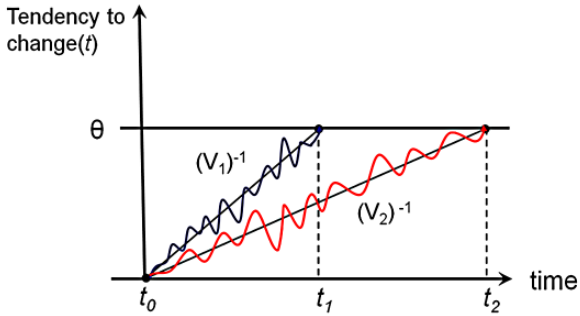

Figure 1. View durations (t_1 vs. t_2) differ for channels with different motivational strengths (V_1 vs. V_2).

diffusion process as described above, which leads to the prediction that the probability distribution of viewing durations at each channel switch should be a Wald destitution (*Hypothesis 3*).[3]

It is worth mentioning that quite intuitively, the mean of the distribution of viewing durations (μ) can be interpreted in terms of the strength of the currently watched channel (v_i) and the threshold bound for changing channels (θ). To see this, consider a simpler case where the variance of the noise is set to zero, $\sigma^2 = 0$. Then the diffusion (or random walk) model is not random anymore, and the motivational strength decays linearly across time like a car traveling at a constant speed for some fixed distance to a destination. In this driving example, calculating the time to reach the destination is familiar to most readers: time = distance/speed. To draw an analogy between the channel changing process and car traveling, the time to travel is analogous with the mean of viewing durations (μ), the distance to travel is similar to the threshold bound (θ), and the speed of travel is the mean rate of motivation decay, which is inversely related to the strength of channel *i* (v_i^{-1}). Thus as mentioned, we have the following relationship between μ, θ, and v_i^{-1}:

$$\mu = \frac{\theta}{v_i^{-1}} = v_i \cdot \theta. \tag{6}$$

This equation is intuitive. If a channel has a larger motivational strength, the viewer's motivation decays more slowly and the viewer stays on the channel longer; and if a channel has a smaller motivational strength, then the motivation decays quicker and the viewer stays on the channel for a shorter time. Thus, the mean of the distribution of viewing durations is directly affected by the motivational strength of the channel. As illustrated in Figure 1, suppose there are two channels, 1 and 2; and channel 1 has smaller motivational strength than channel 2 ($v_1 < v_2$). Then, the motivation decays more quickly while watching channel 1 than watching channel 2. According to

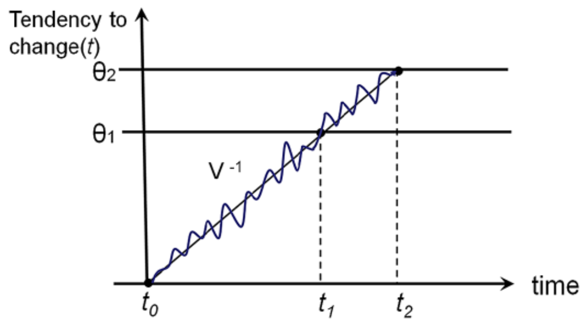

Figure 2. Viewing durations (t_1 vs. t_2) differ for viewers with different thresholds (θ_1 vs. θ_1).

Equation 6, the time it takes to reach the same threshold θ is $t_1 = v_1\theta$ for channel 1 and $t_2 = v_2\theta$ for channel 2, and obviously, the former is shorter because v_1 is smaller.

In addition, viewing durations are determined by the threshold (θ) for switching channels. As introduced above, the Wald distribution shape parameter (λ) is related to the threshold bound in standard deviation units of noise σ, that is, $\lambda = (\theta/\sigma)^2$. With others equal, individuals with a larger value on this parameter will tend to be more persistent and stick to a channel longer even in the face of motivational decay. Higher threshold θ increases λ and produces longer viewing durations. Thus, as portrayed in Figure 2, even with the same channel strength (v), a viewer with higher threshold ($\theta_2 > \theta_1$) stays on the channel longer ($t_2 > t_1$).

Therefore, in addition to rigorous predictions, another benefit of this formal modeling effort is to provide theory-driven individual difference measures. When a large set of channel changing data points are available for each individual, the ChaCha model can be fitted to each individual's data by finding the model parameters that maximize the likelihood of the observed choices and viewing durations. These parameters include the learning rate parameter and the threshold parameter for each individual. It is then possible to examine how these parameters vary across age, gender, ideologies, personalities, and psychiatric symptoms (Busemeyer & Johnson, 2004), which are related with variations in media use and selective exposure, such as channel changing behavior examined here (Lang et al., 2005; Perse, 1990). In the example here, we examine the difference between two age groups: younger versus older adults. In media marketing practice, both are among primary target groups for commercial and prosocial marketing efforts. Theoretically, the ChaCha model can provide cognitive theoretical explanations about *why* media selection varies across age groups that has been observed before (e.g., Knobloch-Westerwick & Hastall, 2010; Lang et al., 2005). Therefore, it is hypothesized that there will be age difference in the cognitive process driving channel changing behavior (*Hypothesis 4*). However, the observed behavioral difference could be caused by differences occur during the reinforcement learning process and/or the diffusion process of choice time, which will be explored and pinpointed (*Research Question*).

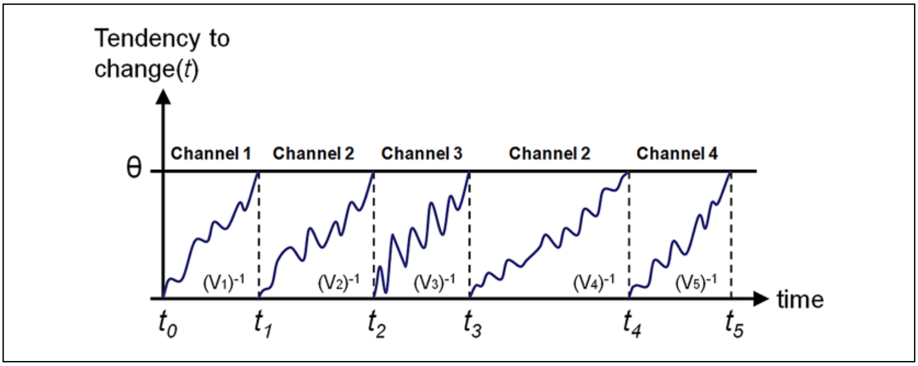

Figure 3. Dynamic changes of the motivational decay process across channels.

The Dynamics of Media Choice Behavior Formalized by the ChaCha Model

The meaning of being "dynamic" is twofold for the ChaCha model. First, *within* one channel, its motivational value and strength continuously changes. That is, the reinforcement learning and decay processes during the viewing of a channel are dynamic and stochastic. They are defined by the updating formulas of motivational values (Equations 2 and 3) and modeled as a diffusion process (Equations 4 and 5). These processes are illustrated in Figures 1 and 2. Second, these processes *across* channels are also dynamic. This is formalized by continuous changes of motivational decays across channels. A viewer may lose interest in a channel (i.e., motivation decays to the threshold) and switch to other channels. After viewing other channels, the viewer may find that the previous channel actually is more interesting compared with other options and switch back to the previous channel because motivational strengths for channels are continuously updated through reinforcement learning. Thus, the differences in motivational values, their updates, and tendencies to switch channels across channels also dynamically change across time. This is illustrated in Figure 3. As shown in an exemplar case in Figure 3, the tendency to switch from channel 2 between t_1 and t_2 changes during t_3 and t_4 because of the cumulative experience from channel 3.

An Empirical Test

The Experiment and the Data

The data used to test the ChaCha model was collected using a 2 (Production Pacing: Fast, slow) × 2 (Story Length: Long, short) × 2 (Age: Younger, older) factorial design experiment (Lang et al., 2005). In the experiment, each participant watched TV newscasts for 15 to 16 minutes. Four news channel options were presented throughout the viewing, during which the participants could use a remote control to switch between channels at will. The four channels were manipulated by the 2 (Production Pacing) × 2 (Story Length) design. Production pacing was manipulated by camera changes. News stories presented on the fast-pacing channels had 13.96 camera changes per minute and those on the slow-pacing channels had only 8.96 per minute. News stories presented on the short story channels lasted 43.3 seconds on average and those on the long story channels were 101.2 seconds on average. Both factors were significant at the $p < .05$ level between the manipulated conditions. Age was the only between-subjects factor. In total, 47 undergraduate students between 18 and 22 years old ($M = 20.4$, $SD = 1.07$) were recruited from a Midwestern university, and 63 adults between 25 and 81 ($M = 44.4$, $SD = 13.8$) were recruited from local community. Participants were randomly assigned to one of the four channel orders. The four orders used a Latin-square design to counterbalance which channel (i.e., the first to the fourth channel) to present which manipulation condition.

The participants viewed the news channels individually in a private room. They were instructed to watch TV as if they were at home and to use a remote to change channels at will. Viewers' sequential channel choices and viewing durations between channel changes were recorded in real-time by a computer connected to the TV set. These data were organized offline in the format as shown in Table 1. One participant from each age group did not make any channel change during the viewing and both were excluded from the analysis.

Parameter Estimation and Model Comparisons

Different specifications of the proposed ChaCha model were compared to test the proposed hypotheses, and they are summarized in Table 2. The full model incorporated all the proposed cognitive processes and contained a separate set of parameters for each age group (labeled the Wald model in Table 2). Then, (a) to test *Hypothesis 1* on the interaction effect of pacing and story length, a competing model excluding the interaction effect (labeled the Wald—No Interaction model) was fitted to the data to make comparisons. (b) To test *Hypothesis 2* on the reinforcement learning process for unselected channels, a competing model without the learning parameter α was formulated as the competing model (labeled the Wald—No Learning model). (c) *Hypothesis 3* predicted that the viewing time distribution was a Wald distribution derived from the diffusion process. It was compared with another well-known response time distribution derived from a Poisson process. According to a Poisson model, there was a small probability for each small unit of time that the person would decide to switch channels. This process would produce an exponential distribution of viewing durations (Townsend & Ashby, 1983),

$$f(t) = \frac{e^{\frac{-t}{v_i}}}{v_i},$$

where $1/v_i$ (or v_i^{-1}) is the rate of occurrence for a person to decide to change channels. The mean of the exponential distribution equals this rate. Thus, like the Wald model, the rate ($1/v_i$) is set equal to the inverse of the motivational strength of a channel so that stronger motivation for a channel produces longer viewing times. This raises the question of whether the diffusion process and its derived Wald distribution better predicts viewing durations than the Poisson process and its derived exponential distribution. To answer this, the full model but with an exponential, instead of Wald, distribution was compared against the Wald model (labeled the Exponential model). Finally, (d) to test *Hypothesis 4* on the age difference and explore where the difference occurred in the cognitive mechanisms, a model using the same set of parameters to fit all individuals' data (labeled the Wald—No Age Differences model) was created to compare with the models using separate parameters for the two age groups.

The models were implemented using MATLAB software and fitted to the data using maximum likelihood methods (Busemeyer & Diederich, 2010). Because the viewing time was relatively short in the experiment, the number of channel changing data points of each participant was relatively small. On average, each participant changed channels around 14 times. Thus, the models were fitted to channel changing data pooled across participants in each age group. The parameters that maximize the log likelihood for each model when it was fitted to the data are used to make model comparisons. Because the models varied in the number of parameters and were not always nested, Schwarz Bayesian Information Criterion (BIC) was calculated for each model to select the preferred model. BIC considers goodness of fit by maximizing the log likelihood of the models and also takes model parsimony into account by giving a penalty to the number of parameters in the model. The BIC uses the *negative* of the log likelihood, which actually is "badness of fit," plus the penalty for model complexity

Table 2. Model Comparisons and Parameters Estimation.

	Model coefficients						Model fit
	Initial	Pacing (fast = 1)	Length (long = 1)	Interact	Learning	Threshold	Model fit
Competing models	B_0	β_1	β_2	β_3	α	θ	BIC
Exponential							
Young	3.92	.62	.87	−1.94	.02	—	10,922.00
Old	3.43	.62	.01	−.14	.03	—	
Wald—No Interaction							
Young	−0.01	.08	−.11	—	.41	3.40	9,270.20
Old	0.01	−.003	−.03	—	−.03	4.20	
Wald—No Learning							
Young	0.01	.13	−.01	−.12	—	4.13	9,279.60
Old	0.003	−.03	.03	.05	—	3.97	
Wald—No Age Difference	0.01	−.03	−.06	.05	−.02	4.24	9,272.60
Wald							
Young	0.11	.02	−.16	.08	.31	3.40	9,268.40
Old	−0.16	−.03	−.04	.03	−.02	4.36	

Note. BIC = Bayesian Information Criterion.

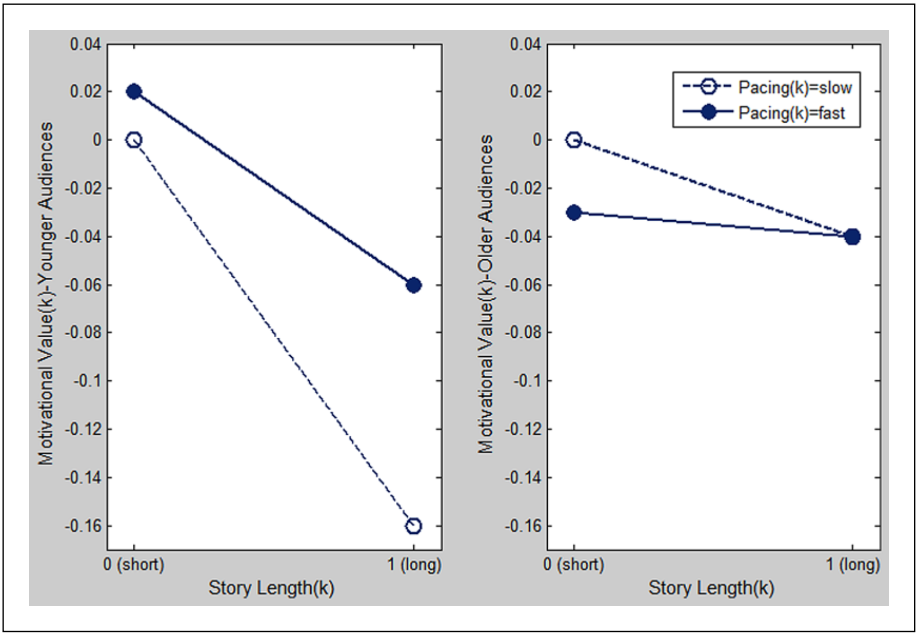

Figure 4. The effects of pacing and story length on motivational values of younger (left panel) and older (right panel) audiences.

(i.e., more parameters), and hence the model with the smaller BIC value is preferred (Busemeyer & Diederich, 2010; Schwarz, 1978).

Modeling Results

The results are summarized in Table 2. As seen, the proposed Wald model with separate parameters for two age groups outperformed all competing models as indicated by its smallest BIC (see the last two rows of Table 2). Therefore, all four hypotheses were supported.

As *Hypothesis 1* predicted, pacing and story length interacted with each other to change motivational values of the channel being viewed. This interaction effect is illustrated in Figure 4. As shown, these two media production features had larger effects on younger than on older audiences. Fast pacing stimulated higher motivational values on younger audiences but lower motivational values on older audiences. Furthermore, pacing moderated the effects of story length on motivational values: For both age groups, the motivational value of a channel was higher when the channel was featured with short news stories, but story length made a larger difference when the production pacing was slow. In particular, for older audiences, when the pacing was fast, the influence of story length became negligible.

As *Hypothesis 2* predicted, when a channel was not viewed, its motivational value was still updated through the reinforcement learning process. Based on the data, the learning rate (or the expected motivational value) α was positive and large for younger audiences (.31) while it was small and negative for older audiences (−.02). This suggests that younger audiences' channel changing behaviors are more likely to be driven by new, unviewed content on unselected channels, while older audiences are more motivated by interests in the currently viewed channel.

Hypothesis 3 on the Wald distribution of viewing durations was also supported. This means that the proposed diffusion process of choice response time is a plausible cognitive mechanism to explain the media choice behavior. More specifically, the threshold parameter θ in the diffusion process was found to differ by age. As seen in Table 2, younger audiences had a lower threshold (3.40) than older audiences (4.36). This indicates that with others equal, younger audiences are more likely to switch channels than older audiences because of lower threshold for motivational decay.

Finally, supporting *Hypothesis 4* on age differences in the cognitive differences underlying the channel choice behavior, the full Wald model with age difference outperformed the same model without age difference (see Table 2). In addition, as discussed above, we answered the *Research Question* by pinpointing the age differences in both the learning rate (or expected motivational value of the unchosen) in the reinforcement learning process and the motivational decay threshold in the diffusion process.

Discussion

This article aims to start to theoretically bridge the motivated information processing and selective exposure behavior, formulate their dynamic reciprocal and recursive influences, and simultaneously predict sequential media choice probabilities and choice response time. As a mathematical and computational specification of the DMA theoretical framework in the context of media choices, the proposed ChaCha model achieves these aims. In the illustrative example, a series of theoretical questions of media choice behavior are examined in the context of TV channel changing.

However, it should be noted that, on the one hand, the ChaCha model is not restricted to the illustrated context. The cognitive mechanisms integrated in ChaCha are abstract and general for the questions under examination and are applicable to a large range of media and information choice phenomena. This is an advantage of formal cognitive modeling compared with statistical modeling. The former formulates and tests specific, fundamental cognitive principles and processes underlying a large range of behaviors; the latter is generic and can be applied to many data sets, but what is learned in one data set cannot be transferred easily to another (Blalock, 1969; Busemeyer & Diederich, 2010).[1] On the other hand, it is worth mentioning that in the first steps of developing a formal cognitive communication model, it is helpful to start with simple scenarios such as the controlled TV viewing experiment in our example. By this way, we are more confident in isolating variables that are directly relevant to testing the proposed cognitive mechanisms. As we have seen, even the "simple" scenario in our example is not simple but rather complex, involving dynamic, nonlinear, and interacting processes. Follow-up studies are in order to further develop and test the ChaCha model so that it can account for more complicated and naturalistic media behaviors (e.g., recorded programs and commercials, media multitasking, actual industry media choice data). The current example, however, indeed illustrates some usefulness of the model to help understand media choice behavior.

The reinforcement learning component of the ChaCha model integrates a viewer's media processing and media selection behavior, which are often studied separately in literature. As the DMA and the ChaCha theorize, the viewer actively selects channels to watch based on motivational values of channel choices. The choice selection behavior alters the viewer's mediated environment, which, in turn, determines her or his media processing experience and subsequent media choices. In our example, consistent with previous research (Lang et al., 2005), two media features, pacing and news story length, are found to influence channel motivational values as perceived by the audiences—especially younger audiences. Our modeling results indicate that younger audiences prefer fast-pacing news, while older audiences prefer slow-pacing news. Both groups prefer shorter news stories, and this effect is moderated by pacing: Short stories are much preferred over long ones when the pacing is slow. When the pacing is fast, the story length makes almost no difference on older audiences.

Interestingly, the change produced by the channel changing behavior on the mediated environment is not limited to the selected channel. Instead, motivational values of unselected channels are also updated. For younger audiences, unselected channels become much more attractive, producing a large, positive expected motivational value. The increased motivational values for unselected channel can lead to interesting dynamics of subsequent behavior: The probability to switch channels increases and time spent on the current channel is shortened. For older audiences, the changes on unselected channels are very small. These findings suggest that younger audiences are more explorative across channels, while older audiences tend to focus on what is currently watched. Recall the debate on active versus passive TV viewing in the literature. Perhaps it is not a simple dichotomous question. Indeed, the reinforcement learning process shows active aspects of TV viewing and channel changing whereas the decay process of motivation suggests certain passiveness. The two mechanisms intricately interact with each other over time to determine the choices and choice times in a nonlinear manner. The ChaCha model untangles them to estimate their effects more accurately. In our example, the model parameters suggest that younger audiences are notably more active during the viewing and channel changing.

The diffusion component of the ChaCha model integrates motivated media choice probability with choice response time (i.e., media use durations). Choice probability and choice response time are interdependent elements of any choice behavior, and together they help more accurately reveal the dynamic mechanisms underlying the choice behavior (Busemeyer & Townsend, 1993; Laming, 1968; Luce, 1986). In the ChaCha model, the diffusion threshold parameter for motivational decay and tendency to change channels is of particular interest. Younger audiences are found to have a lower threshold than the older audiences, which quantifies their greater tendency to switch channels than older audiences. This age difference in motivational decay threshold, together with the age difference in exploring unselected channel choices, help pinpoint specific cognitive mechanisms *why* younger viewers change channels more frequently than older viewers rather than simply describe the behavior (Eastman & Newton, 1995).

As discussed, the proposed ChaCha model is not restricted to the channel changing behavior, but more generally, it should help test and develop theories about media processing and choice. It demonstrates the strength of formal cognitive modeling in building and testing media psychology theories (Blalock, 1969; Busemeyer & Diederich, 2010). First, any media use behavior is a result of complex combination of processes, and the formal model helps untangle these processes and allow them to be taken apart and studied in depth. The ChaCha model untangles the motivated media selection process, the viewer-media interactions, and the motivational changes and decay process; they are specified and formulated using the logistic type of ratio of strength model, the reinforcement learning model, and the diffusion model, respectively. All of these models are rooted in well-established decision and cognitive theories and have been widely tested and applied to many cognitive behaviors (see Busemeyer, Wang, Townsend, & Eidels, in press, for a survey).

Second, the estimated parameters of ChaCha provide theory- and process-based measures of media users' individual differences, such as reinforcement learning rates and motivational thresholds. These measures indicate individual differences in fundamental cognitive mechanisms during media use and provide theoretical explanation about *why* there are variations in observed media choice behavior across individuals or groups. For example, the oft-documented age difference in channel changing behavior may be contributed by age difference occurring during any of the cognitive processes during TV viewing and selection. Using the ChaCha model, this study pinpoints that the difference takes place during both the reinforcement learning and the motivational decay processes, and quantifies the differences in the examined context. This can be useful for advancing our understanding of individual differences that is fundamental to the cognitive mechanisms involved in media use, instead of simply describing differences as observed in media use behaviors and effects. For example, ChaCha can be used to better understand individuals with different sensation-seeking and media-multitasking tendencies.

Third, the model's parameters also can test and predict the effects of various treatment conditions of media content and format features. The model provides deeper scientific understanding of the mechanisms of how media variables, such as production features as illustrated in our example, influence the motivational, cognitive, and decisional processes, and hence determines the observed media selective exposure behavior. For example, ChaCha can be applied to web interface usability tests to evaluate how web design elements can affect users' web browsing choices and browsing durations.

As a first step in developing a formal cognitive and choice model for understanding media processing and selective exposure, a controlled and relatively simplified laboratory experiment is used to illustrate and test the model. Constrained by limited context and limited data points, the current study only illustrates, to a very limited extend, the potentials of the ChaCha model. Refined models should be developed and tested by experiments with longer viewing time and more choice data points. In addition, the model aims to explain a large variety of media choice behaviors. Empirical sequential choice data in various media contexts, such as web surfing, music listening, and daily media use, both in the laboratory and from field research, should be used to further test and develop the model. This is a start toward a coherent cognitive theory of dynamic media choice and processing.

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Notes

1. Formal cognitive models, or cognitive models, are an important theory development and testing tool for understanding cognitive processes that drive human and animal behaviors. In cognitive models, the theoretical assumptions and theorized processes are expressed in formal mathematical or computational languages. This enables the models to make quantitative estimations and predictions for complex processes, including those with complicated interacting and nonlinear components. This feature distinguishes cognitive models from conceptual (verbal) models, which describe their assumptions and processes using natural language. Another feature of cognitive models is that they are derived from cognitive principles, and they are formal theoretical formulations of how cognitive processes work. This means, a cognitive model is specific to the cognitive processes under investigation. This distinguishes cognitive models from statistical models, which are also expressed in formal languages, but are generic and can be generally applied to any data from any field as long as their statistical assumptions (e.g., normality) are met. The statistical assumptions are not derived from cognitive principles and sometimes are even contradictory to cognitive principles (e.g., normality assumption of linear regression models is inconsistent with abnormality of observed choice response time data).
2. Markov models are stochastic dynamic models that formalize how a system transits from one state to another. Markov models are often said to be “memoryless” because they follow the Markov property where the conditional probability distribution of future states depends only on the present state, not on its preceding states, but it is worth pointing out that the present state can include information of its preceding states. The ChaCha model is a semi-Markov model because it predicts not only the choice probabilities of the states (like typical Markov models do) but also the distribution of time between the transitions

(using another different dynamic model, the diffusion model). As described in the article, channel choices can update channel motivational values and strengths through the reinforcement learning process, which are used to determine the state transition probabilities in the Markov model according to the ratio of strength choice model. The state transition time distribution is determined by the diffusion process of motivational decay. Hence, channel choices and choice time are determined by channel motivational values and strengths and also, in turn, reciprocally update them through reinforcement learning.

3. The viewing duration for a channel before switching away from this channel can be any duration greater than 0. It is useful to know how likely each of the possible durations is, that is, the probability distribution of the viewing durations. If the motivational decay and channel switch process is as proposed by ChaCha, a diffusion process, then the viewing duration *at each switch* will have a probability distribution of the Wald distribution. Alternatively, if the motivational decay and channel switch process is a Poisson process (another well-known choice response time model), then the viewing duration *at each switch* will have a probability distribution of the exponential distribution (Townsend & Ashby, 1983). Intuitively, this proposes that *at each switch* of each participant, (a) the viewing time can be any durations greater than 0, but (b) some durations are more likely to occur than the others (i.e., they have different probabilities), and the Wald and exponential distributions predict differently how the probabilities look like. Note that in ChaCha, the choice time distribution prediction is for *each channel switch* of each individual; but, here, to illustrate how the Wald and exponential distributions predict choice time differently, they are fitted to the observed choice time data (i.e., view durations) of all participants. As shown in figure 5 below, although the exponential distribution better fits the viewing durations between 100 and 200 seconds, the Wald distribution can better predict shorter viewing durations, especially the large probability of durations smaller than 60 seconds. In the illustration below, when the distributions are fitted to the choice time data of all participants at once, overall the Wald distribution fits the data significantly better based on the Bayesian Information Criterion (BIC) method. As tested in the article, when being fitted to each channel switch of each individual, the Wald distribution is also preferred based on the BIC method.

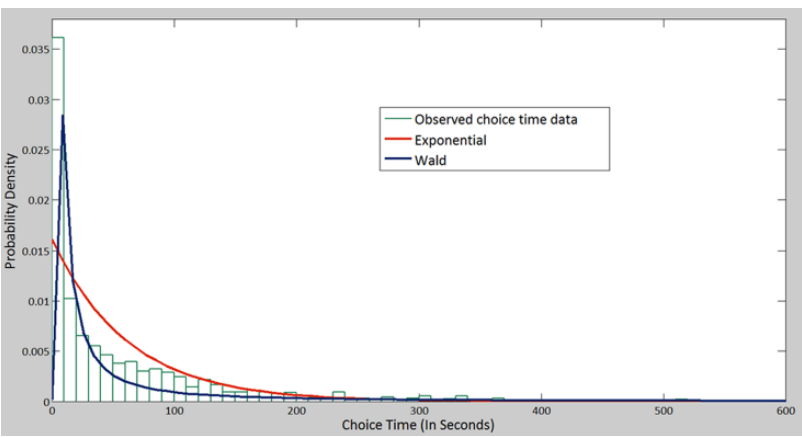

Figure 5. As an illustration, both the Wald distribution and the exponential distribution were fitted to all the choice response time data of all participants. According to BIC, the Wald distribution provides a better fit.

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