

The “Myth” of Media Multitasking:

Reciprocal Dynamics of Media Multitasking, Personal Needs, and Gratifications

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June 29, 2011

Accepted to appear in *Journal of Communication*.

This work was supported by the National Science Foundation (Grant No. SES 0818277). We thank Maria Soufi for her help with data collection. We also thank Editor Malcolm Parks and the three anonymous reviewers for their valuable comments.

Running Head: Reciprocal Dynamics of Media Multitasking

Abstract

The increasing popularity of media multitasking is frequently reported in national surveys while laboratory research consistently confirms that multitasking impairs task performance. This study explores this apparent contradiction. Using dynamic panel analysis of time series data collected from college students across four weeks, this study examines dynamic reciprocal impacts of media multitasking, needs (emotional, cognitive, social, and habitual), and corresponding gratifications. Consistent with the laboratory research, cognitive needs are not satisfied by media multitasking even though they drive media multitasking in the first place. Instead, emotional gratifications are obtained despite not being actively sought. This helps explain why people increasingly multitask at the cost of cognitive needs. Importantly, this study also provides evidence of the dynamic persistence of media multitasking behavior.

Key Words: multitasking, uses and gratifications, dynamic panel models, dynamic reinforcement, neuroticism, experience sampling

Multitasking—engaging in two or more activities at once—is certainly not a new phenomenon. However, media saturation and convergent technologies have made media multitasking increasingly prominent in recent years. A dramatic increase in media multitasking behavior is frequently reported, especially among younger generations. A recent study by Carrier et al. (2009) found that out of 66 possible combinations of media tasks, Baby Boomers (born between 1946 and 1964) had on average engaged in 23.2 combinations, which increased to 32.4 for Gen Xers (born between 1965 and 1978) and 37.5 for Net Geners (born after 1978). Consistent with this acceleration trend, Rideout, Foehr, and Roberts (2010) found that a majority of teenagers multitask “most” or “some” of the time while listening to music (73% of respondents), while watching TV (68%), while using a computer (66%), and while reading (53%). The percentages increased substantially compared to those found in 2004 (p. 34).

In stark contrast to the escalating popularity of media multitasking, growing research evidence consistently confirms its adverse impacts on task performance and learning. For example, while reading a passage from a textbook, students who were simultaneously chatting via instant-messaging took roughly 21% more time compared to those who were not multitasking (Bowman, Levine, Waite, & Gendron, 2010). Watching television while doing academic work has been found to harm performance on both reading comprehension and memory tasks (Armstrong, Boiarsky, & Mares, 1991; Pool, Koolstra, & van der Voort, 2003). Also multitasking has been shown to impair the processing and verification of written information (Gilbert, Tafarodi, & Malone, 1993). Of even greater concern are findings which suggest cognitive deterioration caused by chronic media multitasking. A recent study found that heavy media multitaskers are more distracted by irrelevant stimuli than light media multitaskers and, surprisingly, less efficient at switching tasks (Ophir, Nass, & Wagner, 2009). Furthermore,

multitasking can potentially be life-threatening, as with the complex cognitive demands placed on pilots and drivers (Loukopoulos, Dismukes, & Barshi, 2009).

If multitasking is harming our work performance, deteriorating our cognitive functions, and even threatening our safety, why do we increasingly multitask? Borrowing Rosen (2008)'s words, most perceived benefits of multitasking are only "myths" (p.105). Perhaps people are simply unaware of its actual inefficiencies. Or, perhaps they are forced to multitask by a frenzied work environment. However, from the dynamic motivated choice perspective (e.g., Busemeyer, Townsend, & Stout, 2001; Wang, Lang, & Busemeyer, 2011), there must be positive, reinforcing feedback effects to the behavioral system that originate from underlying motivations. The feedback effects drive and sustain multitasking behavior even when cognitive costs and performance loss occur. This study explores this question using time series data across four weeks of college students' media multitasking behavior, needs, and gratifications. The term "multitasking" has been defined differently as it has been studied on different levels ranging from the cognitive to the behavioral. Here we focus on user-generated conceptions of multitasking (e.g., Ophir et al., 2009) based on self-identified situations that involve two or more simultaneous goals, two or more stimuli, and two or more responses (Meyer & Kieras, 1997). Media multitasking is multitasking involving at least one media-based stimulus or response.

The Uses and Gratifications Perspective

A classic theoretical framework to examine media use behavior and motivation is the uses and gratifications (U&G) theory (Katz, Blumler, & Gurevitch, 1973; for a recent review, see Rubin, 2009). Researchers, viewing the audience as active media users, have used the U&G paradigm to understand the functions served by many new forms of media over the years, from radio to social media networks (Rubin, 2009). The quick diffusion of multitasking-facilitating

media technology, such as smart phones, has provided people with unprecedented convenience and control over when, where, and how they consume media. Hence, a user-oriented theoretical approach is now especially important in understanding people's media choice behavior.

At the center of the U&G approach are the various needs of media users. Needs are “the combined product of psychological dispositions, sociological factors, and environmental conditions” (Katz et al., 1973, pp. 516-517) that motivate media consumption or exposure. Gratifications are the “perceived fulfillment” of the needs through media use (Palmgreen, 1984, p. 22). Because this study focuses on general needs that are relevant across all kinds of media uses and activities, we synthesized commonly used needs from previous typologies (e.g., Katz, Haas, & Gurevitch, 1973; Palmgreen, 1984; Ruggiero, 2000) into four basic categories: emotional, cognitive, social, and habitual. Emotional needs are “needs related to strengthening aesthetic, pleasurable, and emotional experience” (Katz, Haas, & Gurevitch, 1973, p. 166). Cognitive needs are “related to strengthening information, knowledge, and understanding” (p. 166). Social needs are “needs related to strengthening contact with family, friends, and the world” (p. 167). Habitual needs, while sometimes less salient and less active than other needs, can be thought of as ritualized media use driven by needs such as background noise (Katz, Haas, & Gurevitch, 1973) or for structure in one's day (Mendelsohn, 1964).

The Dynamic Reciprocal Influence of Media Uses, Needs, and Gratifications

Implicit in the definition of multitasking (Meyer & Kieras, 1997) is the concept of multiple needs, and thus multiple dynamically changing trajectories of those needs. In fact, even during the process of making a single choice, we are likely to have multiple needs of varying strengths; the relative strengths of the needs will influence which option we select (Busemeyer et al., 2001). Furthermore, the resulting choice behavior, such as consuming a chosen food or using

a chosen media, determines our gratifications, which further influence our needs and subsequent behavior. Early animal behavior researchers have explained how consummatory behavior, such as eating and drinking, reduces the discrepancy between the current and the desired needs, thereby maintaining homeostasis (McFarland, 1971, 1974). These findings have been adapted to explain human behavior dynamics, such as self-regulation (Carver & Sheier, 1981). For example, the dynamics of action theory (Atkinson & Birch, 1970) posits that the dominant action tendency at a given point in time is expressed, leading to satiation, while unexpressed action tendencies grow in strength until a different one becomes dominant.

A similar perspective on dynamic reciprocal influences of choice behavior and needs is shared by media scholars. For example, Slater (2007) proposes a theoretical framework of mutually reinforcing spirals between media uses and effects. He and colleagues found that, for instance, an adolescent with more aggressive tendencies is more likely to watch programming that features aggression and violence, which may further impact his/her aggressive needs and tendencies, potentially leading to a strengthening pattern over time (Slater, Henry, Swaim, & Anderson, 2003). In short, individuals choose and create their environment, including their media environment, but are also affected by this environment. Therefore, to understand media use behavioral patterns and their effects, we need to consider them in a dynamic context which is constantly changed by the media users themselves through their interaction with the environment. This viewpoint resonates with the perspectives of several U&G theorists who have emphasized the distinction between gratifications sought and gratifications obtained (e.g., Palmgreen, 1984). A user's selected media activity may deliver none, some, or all of the gratification sought, and those obtained gratifications, in turn, can lead to adjustments in subsequent choice behavior.

Recently, formal (mathematical) dynamic analyses of real time data have been employed to explore the mutual dynamic influences between media choices, needs, and gratifications. In the context of television viewing, Wang et al. (2006) developed a stochastic model of choices to formalize the motivational utilities (i.e., needs) of channel options, which dynamically change through reinforcement learning of the content presented on different channels. The continuously changing utilities of each channel determine channel choices and viewing durations which, in turn, change the utilities of the channels in real time. Can the dynamic reciprocal impacts between media use and needs, specified and tested by Wang et al. (2006) using laboratory experimental data, be extended to real-life media use? Can the theoretical view of U&G be specified by formal dynamic models? This study attempts to explore these questions and develop dynamic U&G models. To test the dynamic relationship between media multitasking, underlying motivation (as specified by four categories of needs), and corresponding gratifications, we formalize our hypotheses using dynamic panel models (Baltagi, 2008). The dynamic panel model is a powerful tool to parse out the feedback or reinforcement effects of dependent variables, exogenous influences, and heterogeneity across individuals. Three sets of models are hypothesized to predict media multitasking behavior, needs, and gratifications.

The Hypothesized Dynamic Panel Models

The Dynamic Models of Multitasking. A person's media multitasking behavior at any time should be determined by his/her previous multitasking behavior (*Hypothesis 1a*) and his/her needs at the time (*Hypothesis 1b*). Specifically, in the context of our daily media use data, we will explore whether there are daily and weekly reinforcement effects (lag 1 and lag 7 feedback effects, respectively) for media multitasking. Based on the U&G view of active media users and

the literature on motivated choice behavior as reviewed earlier (e.g., Rubin, 2009; Busemeyer et al., 2001), needs are expected to have a positive or increasing effect on multitasking.

In addition, research has shown that personality traits of extraversion (being “dominant, talkative, social, and warm,” McCrae & John, 1992, p. 196) and neuroticism (“the tendency to experience distress,” p. 195) affect multitasking. Introverts were found to have difficulty decoding nonverbal messages while multitasking (Lieberman & Rosenthal, 2001). Neuroticism was found to negatively correlate with multitasking performance (Oswald, Hambrick, & Jones, 2007). In both cases, it is likely that lower ability at multitasking may lead to less multitasking behavior. Thus, we propose that personality differences in extraversion and neuroticism will influence daily media multitasking behavior across individuals (*Hypothesis 1c*). Expressing the hypotheses formally, the full model to be tested is:

$$\begin{aligned}
 & \mathbf{MT}_{i,t} = \alpha_1 \cdot \mathbf{MT}_{i,t-1} + \alpha_2 \cdot \mathbf{MT}_{i,t-7} + \beta_1 \cdot \mathbf{Ne}_{i,t} + \beta_2 \cdot \mathbf{Nc}_{i,t} + \beta_3 \cdot \mathbf{Ns}_{i,t} + \beta_4 \cdot \mathbf{Nh}_{i,t} + \\
 & \mathbf{Extraversion}_i + \mathbf{Neuroticism}_i + u_i + \varepsilon_{i,t} \\
 & \text{for } i = \{1, \dots, N\} \text{ and } \{t = 1, \dots, T\},
 \end{aligned} \tag{1}$$

where N is the number of individuals (panels) in the data set and T is the number of observations (time series) for each individual. In our case, $N = 19$ and $T = 28$. In the above equation, the term $\mathbf{MT}_{i,t}$ on the left hand side of the equation is what we are trying to predict—media multitasking behavior duration for individual i at time point t . The first two terms on the right hand side of the equation, $\alpha_1 \cdot \mathbf{MT}_{i,t-1}$ and $\alpha_2 \cdot \mathbf{MT}_{i,t-7}$, represent feedback effects of prior multitasking behavior from the previous day and a week ago (the coefficients are α_1 and α_2 respectively). These are critical for explaining the time course of the multitasking behavior dynamics as influenced by individual needs and personalities. As illustrated by Wang et al. (2011), small changes in these dynamic system feedback terms can produce striking differences in the system outputs that are

observed by researchers (such as the multitasking behavior) even when the exogenous effects (such as those caused by needs) are kept exactly the same. In other words, the feedback terms determine how quickly the multitasking behavior, as a dynamic system, responds to the changes in needs, and how large and enduring the responses are (Harvey, 1990). Next in the equation are variables representing emotional, cognitive, social, and habitual needs, each with a β coefficient estimating the need's effect on multitasking ($\beta_1 \cdot Ne_{i,t}$, $\beta_2 \cdot Nc_{i,t}$, $\beta_3 \cdot Ns_{i,t}$, and $\beta_4 \cdot Nh_{i,t}$, respectively). The two terms of *Extraversion_i* and *Neuroticism_i* test whether these two traits of individual i affect the media multitasking behavior patterns. Finally, the last two terms are the error terms in the model. Specifically, $\varepsilon_{i,t}$ is the error that is not predicted by the model for individual i at time point t , and u_i includes individual-level effects that we did not or could not measure, called idiosyncratic errors because they vary across individuals.

The Dynamic Models of Needs. Multitasking behavior is proposed to be affected by needs, but how are the needs at any given point in time determined? Needs are hypothesized to be determined by prior needs and gratifications obtained. First, the needs should maintain their endogenous continuity, as suggested by literature on homeostasis (McFarland, 1971, 1974) and cyclical patterns of motivation (David, Song, Hayes, & Fredin, 2007; Wang et al., 2011). This suggests significant positive feedback from the needs themselves across time (*Hypothesis 2a*). As for multitasking, two dynamic system feedback terms are tested—one formalizes the effect of the need from the day before and the other, from one week before. They are specified by $\alpha_{ne1} \cdot Ne_{i,t-1}$ and $\alpha_{ne2} \cdot Ne_{i,t-7}$ in Equation 2, which uses the model of emotional needs (Ne) as an example. In addition, behavior itself can produce gratifications that change needs in real time (Busemeyer et al., 2001; Wang et al., 2006), which suggests a lagged reduction effect from the

gratification on the need (*Hypothesis 2b*). In our model, this is specified by the term $\beta_{ne1} \cdot Ge_{i,t-1}$ in Equation 2, where $Ge_{i,t-1}$ is gratification resulting from multitasking behavior at time point $t-1$ for individual i , and β_{ne1} is its coefficient, which is expected to be negative to produce a reduction effect. Finally, as in the multitasking model, errors within the time series of each individual and across individuals are specified using $\varepsilon_{ne,i,t}$ and $u_{ne,i}$ respectively. It is worth pointing out that for each of the four categories of needs, model coefficients are separately estimated to allow heterogeneous dynamics among different needs. Equation 2 below represents emotional needs (Ne) as an example, which is a function of its feedback effects and lagged emotional gratifications (Ge). The other three categories of needs follow the same formalization.

$$Ne_{i,t} = \alpha_{ne1} \cdot Ne_{i,t-1} + \alpha_{ne2} \cdot Ne_{i,t-7} + \beta_{ne1} \cdot Ge_{i,t-1} + u_{ne,i} + \varepsilon_{ne,i,t},$$

for $i = \{1, \dots, N\}$ and $\{t = 1, \dots, T\}$. (2)

The Dynamic Models of Gratifications. Now we have proposed how needs are affected by gratifications, but what determines gratifications? First, similar to multitasking and needs, there probably is a feedback influence within gratifications across time. However, gratification is a pleasurable emotional *response to* the fulfillment of a need, so gratification seems inherently to be determined by what needs (at what strengths) exist, and by how much a need is fulfilled through behavior. Hence it is less clear whether gratifications, at the daily level in our data, will keep certain persistence despite the exogenous changes in needs and behavior (*Research Question 3a*). As with needs, we will test whether there are feedback effects on gratifications, both daily (lag 1) and weekly (lag 7). Based on the literature on needs and gratifications as reviewed (e.g., Palmgreen, 1984), gratifications are expected to be caused by needs in the same category (*Hypothesis 3b*), by media multitasking behavior (*Hypothesis 3c*), and crucially, by the

interactions between the behavior and needs (*Hypothesis 3d*) because it is the needs-fulfilling behavior that leads to gratifications. Model comparison and coefficient estimation are separately conducted for each of the four categories of gratifications. Using emotional gratifications as an example, Equation 3 depicts the proposed relationships: gratification for individual i at time point t ($Ge_{i,t}$) is determined by emotional needs ($Ne_{i,t}$), media multitasking ($MT_{i,t}$), and their interaction. The model includes the test of feedback effects ($Ge_{i,t-1}$, $Ge_{i,t-7}$). Also, errors within and across individuals ($\varepsilon_{ge,i,t}$, $u_{ge,i}$) are modeled.

$$Ge_{i,t} = \alpha_{ge1} \cdot Ge_{i,t-1} + \alpha_{ge2} \cdot Ge_{i,t-7} + \beta_{ge1} \cdot Ne_{i,t} + \beta_{ge2} \cdot MT_{i,t} + \beta_{ge3} \cdot Ne_{i,t} \cdot MT_{i,t} + u_{ge,i} + \varepsilon_{ge,i,t}$$

for $i = \{1, \dots, N\}$ and $\{t = 1, \dots, T\}$. (3)

Method

The Participants and the Experience Sampling Method

Thirty-two undergraduate students at a large Midwestern university in the United States, recruited through advertising flyers, participated in the study for monetary compensation. Due to time conflicts, three participants withdrew from the study. Because our goal was to examine multitaskers' behavior over time and not the prevalence of multitasking, we excluded 10 people who never or almost never reported multitasking. Of the 19 people whose data are included in the analysis, six (31.58%) were male; 14 (73.68%) were Caucasian and the rest were Hispanic, African American, and Asian. Most were seniors (47.37%) or juniors (42.11%), and the average age was 21.11 ($SD = 1.20$). Those excluded shared similar demographic characteristics.

Using the experience sampling method (Kubey, Larson, & Csikszentmihalyi, 1996), participants reported their activities, both media- and non-media-related, three times per day for four weeks. To facilitate data reporting and to avoid contaminating media use, each participant

was provided with a cellphone-like device to report their activities. The device was configured to only allow email communication between an assigned participant email account (associated with a numeric identity to ensure confidentiality) and a data storage account. Participants were given 1.5-hour windows to submit their reports at midday, in the evening, and before they went to bed. An email reminder was sent to all participants at the beginning of each time window, which triggered a flashing signal light on the device. Before data collection began, all participants were trained for three hours and achieved 100% accuracy in three data reporting tests. Also they were given one day to practice. At the end of the four-week data collection, participants completed questions on demographics, extraversion, and neuroticism (McCrae & John, 1992).

Media Uses, Needs, and Gratifications Measures

Participants were trained to follow a code book to report their activities. The code book was developed based on the U&G literature and a content analysis of open-ended essays on daily activities of undergraduate students over five days ($N = 78$). The code book defines each media activity by the general medium type in use (e.g. computer, radio, print, television, phone) and by specific sub-types within that medium (e.g. for computer-based activities, sub-types included browsing online, social networking, etc.). Non-media activities were divided into categories such as work, learning, recreation, and housework. For each activity, participants reported the type of activity, the duration, and whether any other activities were performed simultaneously. In addition, for each activity or combination of activities (i.e., multitasking), participants provided their motivations for doing the activity/activities from a list of seven potential needs: fun/entertainment, to relax/kill time, information, study/work, social (personal), social (professional), and habits/background noise. For each need, they reported the strength using a 10-point scale (1 means “a teeny tiny need” and 10 means “an extremely strong need”) and

gratifications obtained using a 4-point scale (1 through 4 mean “not satisfied”, “partially satisfied”, “completely satisfied”, and “beyond expectations” respectively). In analysis, the seven categories of needs and gratifications were reduced into four general categories from U&G literature as introduced earlier—emotional (fun/entertainment, to relax/kill time), cognitive (information, study/work), social (personal, professional), and habitual (habits/background noise). Using the more specific categories of needs in data collection helped participants gain more concrete understanding of each need. In analysis, reducing the data to more general categories ensured sufficient data points to model each category, and also made the number of models tested in the study manageable. The content analysis confirmed that these categories covered primary needs and gratifications of college students’ daily activities.

Analysis and Results

Time Series Data Set and Dynamic Panel Data Analysis

For each participant, time series were created for the duration of media multitasking (in hours), the four categories of needs (emotional, cognitive, social, and habitual), and the corresponding gratifications. They were created by averaging data over the three reporting time periods of the day (each period includes around 5-6 hours awake if assuming 8 hours of sleep in a day), resulting in one data point per day and 28 data points in total for each time series. There are within-individual dynamics across time as well as variations across individuals. Dynamic panel models afford simultaneous examinations of both levels of variation while accounting for unobserved individual heterogeneity (Baltagi, 2008). Each of the three sets of hypotheses proposed above was tested by comparing the full model, as specified in the equations, to nested simpler models. We fit the competing models using the generalized method of moments (GMM) estimator implemented by the `xtdpdsys` command of Stata/SE 11.0 software (Arellano & Bover,

1995; Blundell & Bond, 1998). Models were compared using Wald χ^2 (Engle, 1984) and the final selected models passed the Sargan test of overidentifying restrictions (Arellano & Bond, 1991).

The Dynamic Models of Media Multitasking Behavior

Model Fitting and Coefficient Estimation. To test *Hypotheses 1a, 1b* and *1c*, several competing models were compared. Model coefficients and model fit statistics are summarized in Table 1. First, to test whether there are daily and weekly feedback effects of multitasking behavior itself, the full model as explicated in Equation 1 (the L7 model in Table 1), is compared with a simpler nested model without the weekly feedback term (the L1 model in Table 1). As shown in Table 1, the L7 model performs better than the L1 model according to Wald χ^2 , indicating that both the prior day's multitasking activities and those of a week ago help predict multitasking on a given day. Also, the model reveals that cognitive and habitual needs significantly predict multitasking, but emotional and social needs do not. Individual differences in neuroticism affect multitasking, but differences in extraversion do not. Thus, the L7 model is further compared with a simpler nested model excluding the emotional and social needs (Model 3 in Table 1) and an even simpler model excluding extraversion (Model 4 in Table 1). Based on the Wald tests, Model 4 is preferred over the others. [Insert Table 1 about here.]

The Effects of System Feedback, Cognitive and Habitual Needs, and Neuroticism on Media Multitasking Behavior. As predicted by *Hypothesis 1a*, multitasking behavior shows a significant weekly feedback effect as indicated by the Lag 7 feedback term. Supporting *Hypothesis 1b*, daily needs, specifically cognitive and habitual needs, increase multitasking behavior on the day. Coefficients in dynamic panel models can be interpreted in a similar fashion to those in linear regression models, and they provide a static “snapshot” of the estimated effects of the exogenous variables per time unit (though to understand cumulative effects over time,

interpretation is more complex, as discussed below). As estimated by our model coefficients, on average, during a 5-6 hour data reporting time period, when cognitive needs increase by one unit (on the 1-10 scale), media multitasking increases .09 hour; when habitual needs increase by one unit, multitasking increases .07 hour. In addition, neuroticism, but not extraversion, predicts multitasking duration. Thus, *Hypothesis 1c* is partially supported. On average, a participant one unit higher in neuroticism (on the 1-5 scale) than a comparison case is expected to engage in .23 additional hours of media multitasking during a data reporting time window.

The Dynamics of Media Multitasking Behavior across Time. The above analysis shows that media multitasking is a dynamic system with a weekly persistent pattern. For a dynamic system, its responses to an exogenous influence depend on not only the exogenous influence but also the system's own feedback effect. The feedback effect moderates the activation speed, strength, and duration of the exogenous effects in complex ways (Luenberger, 1979; Wang et al., 2011). Thus, to illustrate how the dynamic feedback effects integrate the impacts of needs and traits to determine multitasking behavior *across time*, we put it all together and simulated the integrated effects using the estimated coefficients in MATLAB software.

Following a common analytic strategy in dynamic system analysis, four combinations of the cognitive needs (N_c) and habitual needs (N_h) are selected to systematically demonstrate their effects on multitasking: (1) both are zero (baseline); (2) there is N_c ; (3) there is N_h ; and (4) there are both needs. In our actual data, N_c ranges from 0 to 8.56 ($M = 2.09$, $SD = 1.59$) and N_h ranges from 0 to 6.44 ($M = 1.07$, $SD = 1.16$). Thus, within these ranges, two magnitudes of needs are selected: both at 2 (small needs) and both at their maximum, 8.5 for N_c and 6.5 for N_h (large needs). These two sets of need inputs to the dynamic behavior system are controlled as a step input, which is turned on from zero to a fixed magnitude for a certain duration (in our case, 28

days). After each step input, a 12-day zero setting (i.e., both needs are zero) is used to allow the behavior system to return to its baseline, so we can observe the decay of the behavior when there are not any exogenous influences. As shown in Figure 1, the simulated outcomes of the small needs conditions are plotted in the left panels and those of the large needs conditions in the right panels. At the bottom of the figure, combinations of need inputs are presented in text, with the corresponding step input durations highlighted in grey in the figure. The four rows of panels, from the top to the bottom, represent various neuroticism scores, from very low (Neuroticism score = 1) to very high (Neuroticism score = 4). [Insert Figure 1 about here]

As shown by Figure 1, first, an increase in needs—cognitive, habitual, or both—causes an increase in multitasking. Cognitive needs have a greater impact than habitual needs. Second, across the neuroticism differences, increased neuroticism increases multitasking. Third and probably most interestingly, the appearance of a new need (i.e., time points 40, 80, and 120) does not instantaneously activate media multitasking behavior, and the disappearance of a need (i.e., time points 68, 108, and 148) does not immediately deactivate it either. Instead, because multitasking behavior is shaped by its own past responses, it takes time to react to changes in needs, showing a gradual increase/decrease to reach equilibrium.

The Dynamic Models of Needs

Model Fitting and Coefficient Estimation. To test *Hypotheses 2a* and *2b*, two competing models were compared for each of the four categories of needs: (1) the proposed full model as presented in Equation 2 (the L7 model in Table 2); and (2) a simpler nested model without the weekly feedback term (the L1 model in Table 2). As seen in Table 2, interestingly, a model incorporating weekly feedback is the best fit only for cognitive needs; whereas, for the

other three categories of needs, models that incorporate daily (but not weekly) feedback are preferred. [Insert Table 2 about here.]

The Effects of System Feedback and Lagged Gratifications on Needs. Supporting *Hypothesis 2a*, each category of needs has a significant feedback effect, and all the feedback coefficients are positive, which indicates persistence or continuity of needs across time. The lag 7 feedback effect of cognitive needs suggests a weekly pattern in this category of needs, which may relate to the fact that our participants are college students with weekly structured study and work schedules. More interestingly, the lag 1 feedback coefficients are consistently between .30-.35 across all categories of needs. This suggests rather stable trajectories of these needs across time: around one third of the amount from the previous day is carried over to the next day, which in turn, is further integrated into the day after. Thus, any exogenous influence on the needs, as integrated by the system's feedback, can be relatively enduring. Supporting *Hypothesis 2b*, for all four categories of needs, lagged gratifications showed a significant negative or reducing effect on the needs. The coefficients allow us to quantify the influence of one day's gratifications on the next day's needs. Among the four categories, cognitive gratifications showed the largest effect: increasing daily cognitive gratifications by 1 unit (on the 1-4 scale) will reduce cognitive needs by .74 unit (on the 1-10 scale) on the next day. Social gratifications showed the smallest effect: a 1 unit increase will reduce social needs by .44 unit on the next day.

The Dynamics of Needs across Time. On a larger scale across many days, to illustrate how the system feedback effects of needs accumulate and moderate the impact of lagged gratifications to change the needs over time, we simulated their integrated effects based on coefficients in Table 2 (see Figure 2). Within the range of the actual data, five inputs of gratifications are selected: 0 (baseline), 1 (not satisfied), 2 (partially satisfied), 3 (completely

satisfied), and 4 (beyond expectations). Again, the inputs are controlled as a step input. The four panels, from the top to the bottom, respectively depict emotional, cognitive, social, and habitual needs. [Insert Figure 2 about here]

As shown in Figure 2, across four categories of needs, a clear pattern emerges. First, an increase in gratifications reduces the needs of the same category. Second, this reduction in needs does not occur instantaneously upon gratification. This is evident at the onset of the gratification (i.e., time points 40, 80, 120, and 160): needs take a while to subside—in our case, two or three time points—even after gratification. Third, needs remain low after gratification ceases (i.e., time points 68, 108, 148, and 188) for a few time points before they gradually increase to reach the baseline level. Importantly, all of these findings illustrate the dynamic, history-dependant nature of needs as tested by the system feedback terms. Finally, looking at individual needs, the dynamic trajectory of cognitive needs (the second panel) is more complicated compared to the other needs because of the additional influence from the lag 7 or weekly feedback effect.

The Dynamic Models of Gratifications

Model Fitting and Coefficient Estimation. Two competing models were compared for each category of gratifications: (1) the proposed full model as presented in Equation 3 (the L7 model in Table 3) and (2) a simpler nested model without the weekly (i.e., lag 7) feedback term (the L1 model in Table 3). As shown in Table 3, based on Wald χ^2 , the L1 model is preferred for all four categories of gratifications. [Insert Table 3 here]

The Effects of System Feedback, Needs, and Media Multitasking Behavior on Gratifications. Heterogeneous patterns across the four categories of gratifications are found for *Research Question 3a*. Only for emotional gratifications, there is significant lag 1 or daily feedback effect, and the positive coefficient (.06) suggests a small cumulating effect. The other

three categories are not affected by their own feedback, at least on the daily level. However, as predicted by *Hypothesis 3b*, consistently across all four categories, needs significantly determine gratifications. The coefficients range from .29 for cognitive gratifications to .38 for emotional gratifications (see Table 3), which suggests that on average, a one unit increase in needs (on the 1-10 scale) will increase gratifications in the same category by .29 to .38 units (on the 1-4 scale).

As predicted by *Hypotheses 3c* and *3d*, media multitasking shows a positive effect on gratifications and it interacts with needs; but interestingly, this is only found for emotional and habitual gratifications (see Table 3). In our data, participants multitasked 0 to 3.83 hours ($M = .49$, $SD = .68$) during each 5-6 hour time period; emotional needs ranged from 0 to 8.60 ($M = 2.53$, $SD = 1.71$) and habitual needs, as reported earlier, ranged from 0 to 6.44. The model illustration in Figure 3 is consistent with the actual data. As seen in the figure, emotional gratifications at any time point for an individual increase as emotional needs increase. Interestingly, when emotional needs are relatively low, an increase in multitasking boosts the gratifications; however, when emotional needs become higher (> around 4.2 on the 1-10 scale), the effect of multitasking on gratification reverses and an increase in multitasking reduces gratifications. Similar patterns are found for habitual gratification except that only when habitual needs are very low (< around 1.6), multitasking increases gratifications. [Insert Figure 3 here]

Discussion

This study specified dynamic uses and gratifications in everyday media multitasking among college students, and tested the reciprocal impacts of media multitasking, needs, and gratifications. These help explain “the myth of multitasking” (Rosen, 2008, p.105).

Reciprocal, Dynamic Impacts of Needs, Media Multitasking, and Gratifications

As proposed by the classic U&G perspective, media multitasking behavior is driven by individuals' needs at the time. More importantly, however, the behavior also reciprocally changes needs. As predicted by dynamic theories of motivation and choice behavior (Busemeyer et al, 2001; Wang et al., 2011) and our specification of dynamic U&G models, media multitasking increases gratifications, which in turn, reduces needs in real time. Interestingly, media multitasking behavior is driven by cognitive needs which are not gratified by the behavior. This finding is consistent with the large body of laboratory research on the impairment of multitasking on cognitive task performance. It is worth noting—and worrisome—to see that the laboratory evidence extends to the real life realm.

Then why do people increasingly multitask at high cognitive costs? This study suggests at least two reasons. First, although cognitive needs are not gratified by media multitasking, emotional needs are, such as feeling entertained or relaxed. To add a twist, emotional needs are not actively sought in media multitasking. Thus, emotional gratifications appear to be a “byproduct” obtained from the behavior. How does this occur? While our model cannot provide information about specific activities, it suggests that if participants were, for example, studying for a test while watching TV, their multitasking might lead them to feel satisfied not because they were effective at studying, but rather because the addition of TV made the studying entertaining. In the long run, it is likely that this emotional gratification associated with multitasking serves as an implicit yet powerful drive, similar to the formation of implicit attitudes through classical conditioning (Olson & Fazio, 2001), to engage the students in media multitasking again and again. In this sense, the “myth” of multitasking actually is partially caused by the “misperception” of the efficiency of multitasking and by positive feelings associated with the behavior, which is emotionally satisfying but cognitively unproductive.

Meanwhile, it is interesting to note that emotional gratification itself is a function of emotional needs and multitasking (see Figure 3). Multitasking increases emotional gratification when emotional needs are low, but it decreases emotional gratification if the needs are high.

Second, habits play an important role in media multitasking behavior, and multitasking can be self-reinforcing. Our findings show that habitual needs increase media multitasking and also are gratified from multitasking. More importantly, our dynamic analysis found a significant feedback effect of the media multitasking behavior. This feedback effect integrates past media multitasking experience into the current situation, and accumulates all the exogenous influences from needs and gratifications to reinforce the behavior. In addition, needs and gratifications themselves are self-generating and self-reinforcing as indicated by their own significant feedback terms. Thus, the habitual continuation of media multitasking behavior is further strengthened, in a more complicated way, by self-reinforcing needs and gratifications.

Personality Traits and Media Multitasking

Prior research highlights two personality traits that may impact multitasking: extraversion and neuroticism. Our study did not find evidence for extraversion. It is possible that extraversion only impacts multitasking in certain situations, such as when the cognitive load on participants is very high (e.g., Oswald, et al., 2007). Extraversion is associated with easier multitasking because of greater working memory capacity (Lieberman & Rosenthal, 2001). Hence, it may lead to greater success in demanding situations, but may be less relevant for self-selected media multitasking behavior, which generally does not require the full capacity of working memory.

Our study found that students with higher neuroticism are more likely to engage in media multitasking. This may appear to contrast with findings by Oswald et al. (2007). They found that in a visual-auditory multitasking, neuroticism was negatively correlated with performance.

However, it is possible that the tendency to experience anxiety that features neuroticism may decrease abilities for demanding tasks, such as the task used by Oswald et al. (2007), but not self-selective daily media tasks. This explanation seems more plausible considering previous findings that individuals' sensation seeking tendency is positively correlated with everyday media multitasking (Jeong & Fishbein, 2007), and the disinhibition dimension of sensation seeking is positive correlated with neuroticism (Zuckerman et al., 1993). Future research can further explore the mechanism of disinhibition and neuroticism in media multitasking choices.

Limitations and Implications

Several limitations of the study should be noted. First, in specifying a general model of media multitasking, we necessarily omitted distinctions between specific activities, and between the copious different possible combinations of activities. However, depending on task features and media features, the dynamics of media uses and gratifications are likely to vary. Second, we only examined four general, overarching categories of needs and gratifications. For each of them, more specific categories, such as different types of emotional needs, may play different roles in media multitasking. Future studies—with a larger data sample—can identify meaningful distinctions within these areas. Third, our experience sampling method relies on self-report measures. Future research can couple experience sampling with behavioral measures, such as cognitive task performance, to test reported versus actual multitasking efficiency.

In addition, future research can investigate long-term effects of chronic media multitasking on a representative sample of participants. Our study found evidence of the persistence of multitasking behavior and of the intricate dynamic reciprocal impact between this behavior and individuals' needs and gratifications. Like a locomotive picking up steam, these self-reinforcing processes, together with moderating individual traits, might lead to significant

long-term effects on individuals. For example, research has suggested that chronic media multitasking can impair cognitive functions (Ophir et al., 2009). Considering the expansion of our information environment through media technologies in the past decades, it is critical to carefully examine the long-term mutual influences of media multitasking, cognitive functions, and personal traits from a dynamic, developmental perspective.

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Table 1. Model Evaluation and Estimated Coefficients for Competing Media Multitasking Models

	MT _{<i>i,t</i>}			
	L7 Model	L1 Model	Model 3	Model 4
	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>
Intercept	-1.81 (1.05) [†]	-2.02 (.98)*	-1.78 (1.04) [†]	-.47 (.32)
MT _{<i>i,t-1</i>}	.05 (.04)	.05 (.04)	.05 (.04)	.05 (.04)
MT _{<i>i,t-7</i>}	.12 (.05)*		.12 (.05)*	.12 (.05)*
Emotional Need _{<i>i,t</i>}	.01 (.02)	-.01 (.02)		
Cognitive Need _{<i>i,t</i>}	.10 (.03)*	.07 (.02)*	.09 (.02)*	.09 (.02)*
Social Need _{<i>i,t</i>}	.001 (.03)	-.03 (.03)		
Habitual Need _{<i>i,t</i>}	.07 (.03)*	.06 (.03)*	.07 (.03)*	.07 (.03)*
Extraversion _{<i>i</i>}	.39 (.30)	.48 (.27) [†]	.39 (.29)	
Neuroticism _{<i>i</i>}	.22 (.12) [†]	.25 (.12)*	.22 (.12) [†]	.23 (.12)*
Wald χ^2	34.08*	27.56*	34.82*	33.26* ^a

* $p < .05$, [†] $p < .10$; ^a indicates the model is preferred, which is selected based on the p -value associated with the Wald χ^2 value difference between the two competing models (df = the difference of the number of coefficients of the two competing models).

Table 2. Model Evaluation and Estimated Coefficients for Competing Needs Models

	Emotional Needs _{i,t}		Cognitive Needs _{i,t}		Social Needs _{i,t}		Habitual Needs _{i,t}	
	L7 Model	L1 Model	L7 Model	L1 Model	L7 Model	L1 Model	L7 Model	L1 Model
	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>
Intercept	2.11 (.18)*	2.45 (.12)*	1.50 (.14)*	1.97 (.10)*	.68 (.07)*	.73 (.05)*	.99 (.08)*	1.01(.06)*
Need _{i,t-1}	.24 (.12) [†]	.30 (.10)*	.33 (.10)*	.41 (.09)*	.25 (.11)*	.30 (.10)*	.26 (.10)*	.35 (.09)*
Need _{i,t-7}	.08 (.05) [†]		.22 (.05)*		.10 (.05)*		.07 (.05)	
Gratification _{i,t-1}	-.34 (.33)	-.60 (.28)*	-.74 (.30)*	-.97 (.27)*	-.33 (.28)	-.44 (.25) [†]	-.44 (.24) [†]	-.63 (.22)*
Wald χ^2	12.43*	8.78* ^a	38.92* ^a	21.77*	18.77*	17.93* ^a	13.61*	18.07* ^a

* $p < .05$, [†] $p < .10$; ^a indicates the model is preferred, which is selected based on the p -value associated with the Wald χ^2 value difference between the two competing models (df = the difference of the number of coefficients of the two competing models).

Table 3. Model Evaluation and Estimated Coefficients for Competing Gratifications Models

	Emotional Gratification _{i,t}		Cognitive Gratification _{i,t}		Social Gratification _{i,t}		Habitual Gratification	
	L7 Model	L1 Model	L7 Model	L1 Model	L7 Model	L1 Model	L7 Model	L1 Model
	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>
Intercept	.07 (.03) [†]	.04 (.03)	.16 (.03)*	.16 (.03)*	.05 (.02)*	.06 (.01)*	.10 (.02)*	.08(.02)*
Gratification _{i,t-1}	.03 (.01)*	.06 (.02)*	-.01 (.02)	-.01(.02)	.02 (.02)	-.005 (.02)	-.02 (.02)	-.01(.02)
Gratification _{i,t-7}	-.02 (.02)		-.03 (.03)		.01 (.02)		-.01 (.03)	
MT _{i,t}	.08 (.02)*	.08 (.03)*	-.03 (.04)	-.04 (.03)	-.01 (.02)	.003 (.02)	.04 (.02)*	.04 (.02)*
Need _{i,t}	.39 (.01)*	.38 (.01)*	.29 (.01)*	.29 (.01)*	.36 (.01)*	.36 (.01)*	.37 (.01)*	.37 (.01)*
MT _{i,t} × Need _{i,t}	-.03 (.01)*	-.02 (.01)*	-.002 (.01)	.002 (.01)	.02 (.01)	.01 (.01)	-.04 (.01)*	-.03 (.01)*
Wald χ^2	2148.75*	2397.10* ^a	1264.75*	1546.92* ^a	1842.72*	1958.87* ^a	1251.65*	1618.07* ^a

* $p < .05$, [†] $p < .10$; ^a indicates the model is preferred, which is selected based on the p -value associated with the Wald χ^2 value difference between the two competing models (df = the difference of the number of coefficients of the two competing models).

Figure 1. Daily Media Multitasking (in Hours) as a Function of Its Lag 7 Feedback Effect, Cognitive Needs (Nc), Habitual Needs (Nh), and Individual Neuroticism (Neu) across Time.

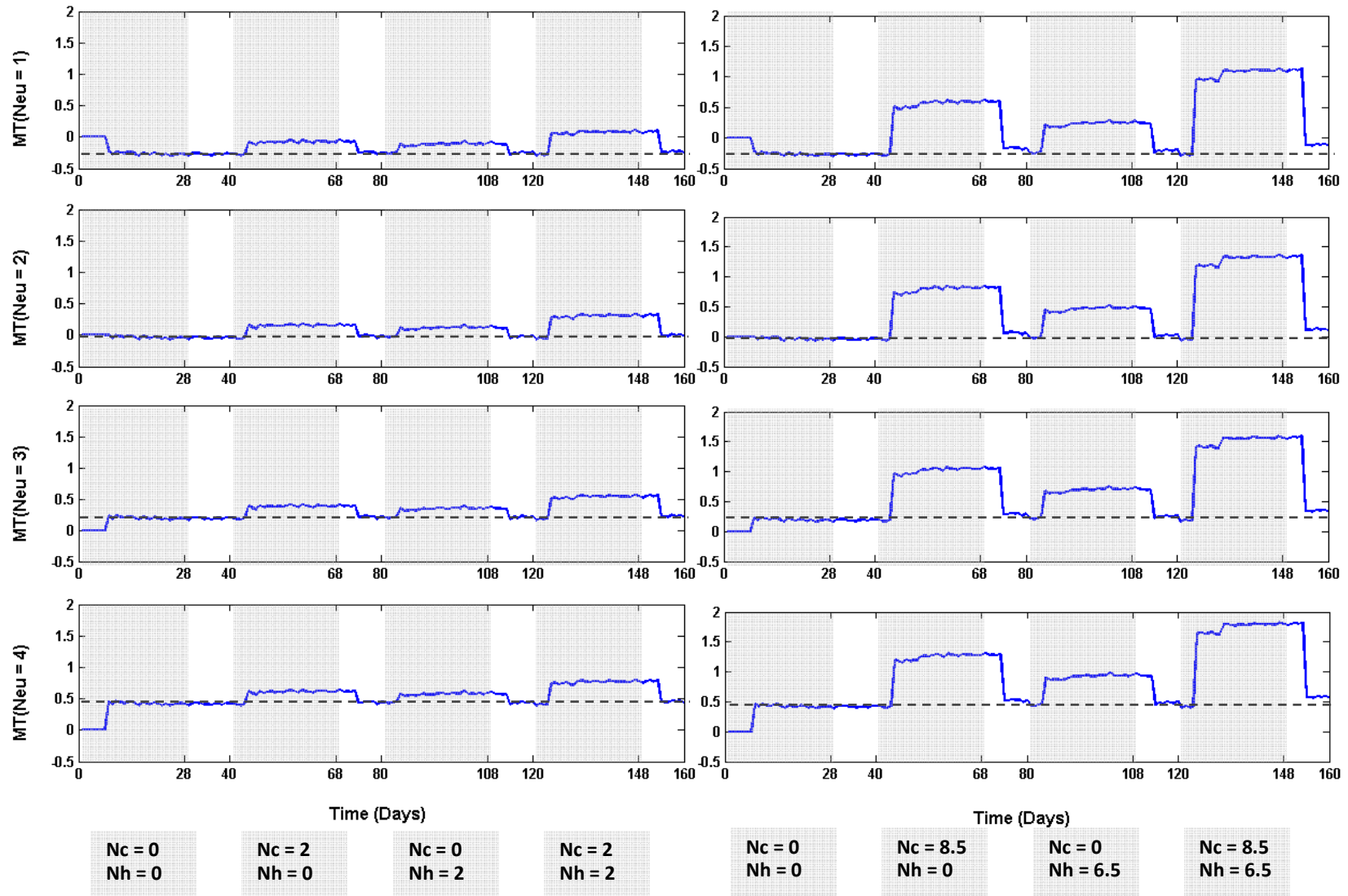


Figure 2. Needs as a Function of System Feedback Effects and Lagged Gratifications Influences across Time.

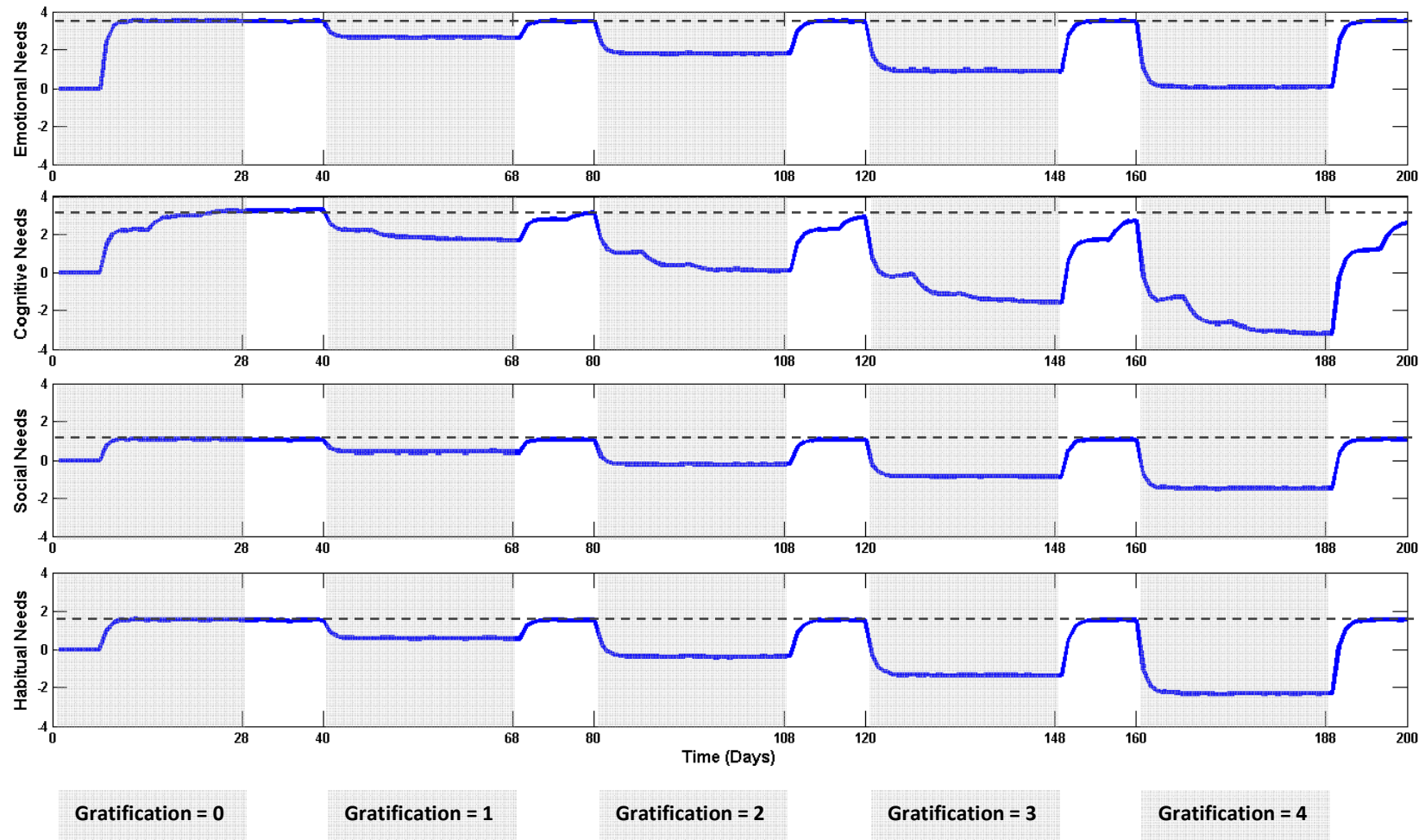


Figure 3. Emotional (Left Panel) and Habitual (Right Panel) Gratifications as a Function of Needs and Media Multitasking Behavior.

