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Control Dimensions of Media Task-Switching and Emotional Well-Being

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Abstract

Frequent task-switching between communication media is ubiquitous. Recent research on the topic highlights that multiple dimensions compete to predict task performance and productivity while multitasking. However, the emotional impact of task-switching is understudied and is an important outcome for understanding communication technology use and its potential effects on people's well-being. This research used ecological momentary assessment (EMA) to gather task-switching and emotional data in real-time through a smart phone application. The emotional effect of the task control multitasking dimensions was assessed via a structural equation model. Results show attitudes toward task-switching moderate emotional valence, but arousal increases with frequency of task-switches. Furthermore, attitudes toward task-switching do not predict frequency of task-switches, contrary to assumptions made in previous research and indicating a loss of control of task-switching behaviors.

Keywords: mobile communication, emotional well-being, digital media, multitasking

Introduction

Media task-switching, the sequential processing of media, and multitasking, the parallel processing of media, have become stable programs of research in the areas of communication technology and media psychology. Recent data show smartphone users switch apps an average of 101 times per day and about four times during each smartphone session (Deng et al., 2018). Yeykelis et al. (2014) show switches occurred every 19 seconds on a laptop. Highly agile media use has prompted concern for people's task performance and well-being. Fitz et al. (2019) report that increased cognitive load from continuous distractions on mobile devices can lead to a sense of losing control, reduced attention, and lower perceived productivity. However, evidence shows that task-switching behaviors have become a habit for many (Hwang et al., 2014; Judd & Kennedy, 2011; Ophir et al., 2009).

Early multitasking research focused on the negative performance losses of split attention and concentration on primary tasks, but as faster, more connected devices became accessible, research on multitasking behaviors shifted to identify the potential benefits of task-switching. By recognizing the "paradoxical cost of multitasking" (Katzir et al., 2018, p. 24), researchers can weigh the real downsides of multitasking against the equally real task, emotional, and social gains of rapid media consumption and constant communication. To this end, Wang et al. (2015) offer 11 dimensions by which media multitasking can be organized. This advancement in theory allows a more nuanced, multi-dimensional approach to assessing the effect task-switching has on people's productivity. However, effects of multitasking on a person's well-being remains a salient and contested topic (Anderson & Rainie, 2018).

In this study, we look at the task switch dimension from Wang et al. (2015) which focuses on the control a person has over their media consumption. By investigating this concept, we seek to apply a productivity-oriented theory to the topic of well-being and communication technology. We examine the ability to control task-switching by testing the relationship between self-reported preference for task-switching and participants' actual task-switching practices as measured through ecological momentary assessment (EMA). This method of measuring media use and response offers an alternative to privacy-invasive observation and tracking tools (Couldry & Mejias, 2018) without the same limitations of cross-sectional surveys. Second, we assess measures of emotional arousal and valence as possible outcomes of task-switching to compare the effects of mediated task-switching on one dimension of well-being: emotional response.

Literature Review

Dimensions of Media Task-Switching

Multitasking and task-switching exist along a continuum between parallel processing to sequential processing (Benbunan-Fich et al., 2011; Salvucci & Taatgen, 2011; Yeykelis et al., 2014). Listening to music while working on homework would be considered multitasking. Momentarily stopping homework to respond to a text message is task-switching. The focus of this research lies between the extremes of this continuum. Cognitive research suggests complete parallel processing is difficult if not impossible to achieve (Bluedorn et al., 1992; Salvucci & Tattgen, 2011) and research on media use shows individuals often attend to more than one mediated task at a time (Calderwood et al., 2014).

Because of the variety of combinations of media tasks and frequencies of switches, a more helpful way to organize multitasking and task-switching is to recognize the control people assert over their media behaviors. Wang et al. (2015) developed 11 dimensions of media multitasking to better address the breadth of experiences during any one media session. These dimensions answer the questions, "How are the two tasks related to each other? (Task Relevance) How is a task information presented to the user? (Task Inputs) Is any behavioral response required by the task? (Task Outputs)" and "Do difference in users affect the processing of and response to the tasks? (User Differences)" (Wang et al., 2015, p. 106). One of the task-related dimensions is task switch, which is the primary focus of this study.

The task switch dimension "captures the extent of control people have over switching between tasks" (Wang et al., 2015, p. 109). This control can be limited by the media format—whether a video can be paused—or can be motivated by an individual's motivations. Fitz et al. (2019) found that checking mobile device notifications associated with motivations like Fear of Missing Out (FoMO), mindfulness, and nomophobia (the fear of being without a mobile device), and external aspects like enjoyment of a task, anxiety, and social pressures. These correlations were found to vary if mobile device notifications were batched or eliminated and controlled whether these changes in experience led to positive outcomes like reduced stress, happiness, or increased perceived productivity. For example, when notifications were reduced FoMO ratings and anxiety increased substantially. More notifications alleviated FoMO even if the distractions reduced perception of productivity.

Some research shows that people are aware of these trade-offs when switching tasks and actively balance these competing motivations to create and control their media experiences. Yeykelis et al. (2014) argue that people consider alternative tasks while engaged in an activity and anticipate when they might switch to something else to meet an alternate goal. Cognitive behavioral research by Katzir et al. (2018) propose and provide empirical support for optimal suppression, a strategy by which a person selectively tunes out irrelevant stimuli from multiple tasks to better handle relevant stimuli. Katzir et al. argue optimal suppression is "global in a sense of adopting a strategy that adapts to the context at which one operates" (2018, p. 36). In other words, they found people are good at deciding, across various scenarios, what information to attend to so they can quickly and successfully complete consecutive tasks. This ability was questioned in earlier cognitive research on multitasking (Meiran et al., 2010).

Behavioral research similarly shows people's sensitivity to contextual motivations and payoffs when deciding when to multitask. Xu et al. (2016) conducted a cross-sectional survey that asked about multitasking tendencies and three measures of well-being. They found multitasking during entertainment media activities significantly increased social success, self-control, and sense of normalcy. Multitasking during synchronous social interactions decreased social success but had no significant effect during asynchronous social interactions. Interestingly, respondents reported multitasking most frequently with entertainment media and asynchronous social behaviors. Xu et al. (2016) argue that not only can multitasking be beneficial to well-being, but also that people make decisions in line with the most beneficial outcomes.

When users are viewed as motivated agents who control their media consumption and are quite well-adapted for selective attention, the questions driving media task-switching research change from whether modern media behaviors are good or bad to determining what people get out of task-switching and how devices and system designs can empower optimal choices. For this study, we first look at a major factor of task-switching, a person's attitude toward task-switching and whether this attitude controls how often people switch tasks.

Attitudes toward Task-Switching

Individuals hold various attitudes toward the practices of task-switching (Ophir et al., 2009). Many studies on academic and workplace performance have identified the differential effects of multitasking on so-called heavy media multitaskers and light media multitaskers. This work has shown largely negative results of task-switching (Carrier et al., 2009; Jacobsen & Forste, 2011; Kraushaar & Novak, 2010; Levine et al., 2007; Pool et al., 2003). Despite the negative trend, recent studies suggest an inverse U-shaped association between number of tasks and productivity (Adler & Benbunan-Fich, 2012) and that productivity decreases across tasks relying on the same sensory resources (Wang et al., 2012). Additionally, task-switching and multitasking have been linked to a narrowing of attentional focus during information processing (Kazakova et al., 2015). There is also evidence that individual differences in intelligence, scholastic aptitude, and working memory predict multitasking ability (Colom et al., 2010; Morgan et al., 2013). Although it is suggested that intelligence and working memory affect task-switching skill, the question of whether heavy media task-switchers perform better than light media task-switchers is debated (Alzahabi & Becker, 2013).

With the knowledge that differences exist between media users, many research designs incorporate measures of task-switching preference to separate individuals based on their attitudes on media-use. A common practice is to separate heavy task-switchers from light task-switchers using Ophir et al.'s (2009) Media Multitasking Index (MMI) (Alzahabi & Becker, 2013; Baumgartner et al., 2014; Jeong et al., 2010; Pea et al., 2012; Ralph et al., 2015). The MMI measures a person's frequency of media use "during a typical media-consumption hour" (Ophir et al., 2009, p. 15586). The data from the MMI is then used to divide samples based on an assumption that heavy task-switchers possess attitudes or traits that distinguish them from others with different usage patterns.

The assumption that task-switching preference predicts actual task-switching has been infrequently assessed. Brasel and Gips (2011) used Waller’s (2007) multitasking preference scale and found a weak but significant relationship between individual preference and number of switches in a laboratory setting. More recent evidence suggests a habitual approach may better predict media use (Naab & Schnauber, 2016). Testing this often-assumed motivation is our first research question. If user control over task switches moderates the effects of task-switching, then those who like task-switching should engage in the activity more frequently. However, if task-switching is habitual, the preference and behavior may not correlate and the lack of motivated control of the task-switch dimension may lead to more negative effects on well-being.

RQ1: Do attitudes toward task-switching correlate with actual task-switching behavior?

Task-Switching’s Effect on Arousal and Valence

Even though research has shown the negative effects of task-switching on productivity, more research is now being published on non-productive motivations for task-switching. Wang and Tchernev (2012) found emotional needs were met through media multitasking, even while cognitive needs were not. In a similar study, Hwang et al. (2014) found enjoyment was a significant predictor of online task-switching, but different sets of motivations were associated with different types of media task-switching. To further this research, this study will look at one dimension of well-being, emotional valence and arousal.

Foundational to this study is the theoretical framework of limited cognitive capacity and motivated message processing (Lang, 2000, 2006). This approach states cognitive resources are limited and must be purposefully allocated when demand for resources outpaces available resources (Basil, 1994). Wang et al. (2015) describe this as the "law of less work." In situations where individuals attend to multiple tasks in sequence, the media user controls which information to process. These decisions are not made rigidly but instead fluidly and automatically (Salvucci & Taatgen, 2008, 2011). Some factors, such as modality of information, necessarily limit allocation possibilities (De Jong & Sweet, 1994; Pashler, 1994; Wang et al., 2015). For example, the eyes cannot be used to read two texts at once but listening to music while reading is possible because the auditory and visual channels can be used simultaneously. Also influencing processing decisions are the emotional attributes of the content and of the individual. Valence and arousal play importantly into this process because of their close relationship with the appetitive and defensive motivations (Bolls et al., 2001; Lang & Bradley, 2010).

Valence

A common operationalization of valence is the positive or negative value of emotion (Bolls et al., 2001). Enjoyment, contentedness, and happiness are characteristics of positive valence. Negative valence is associated with depression, sadness, or displeasure. Individuals who view content that is pleasurable respond with reports of positive valence using both self-reported and physiological measures (Lang & Bradley, 2010). This study did not record the valence of the content participants viewed, but instead the response to their entire media consumption sessions and level of task-switching. However, we expect valence to tend toward positive, especially as social media can be an intrinsically pleasurable activity (Reinecki et al., 2014).

The findings of Wang and Tchernev (2012) and Hwang et al. (2014) suggest individuals who fulfill their motivations to task-switch should experience an appetitive reward. This would manifest through emotions aligned with positive valence. This effect is likely to only be present in people who view task-switching as a positive activity. For those who hold negative attitudes toward task-switching, engaging in the activity would be met with displeasure and negative valence.

This expectation serves as the foundation for the first hypothesis.

H1: Attitudes toward task-switching will moderate the relationship between valence and actual task switching.

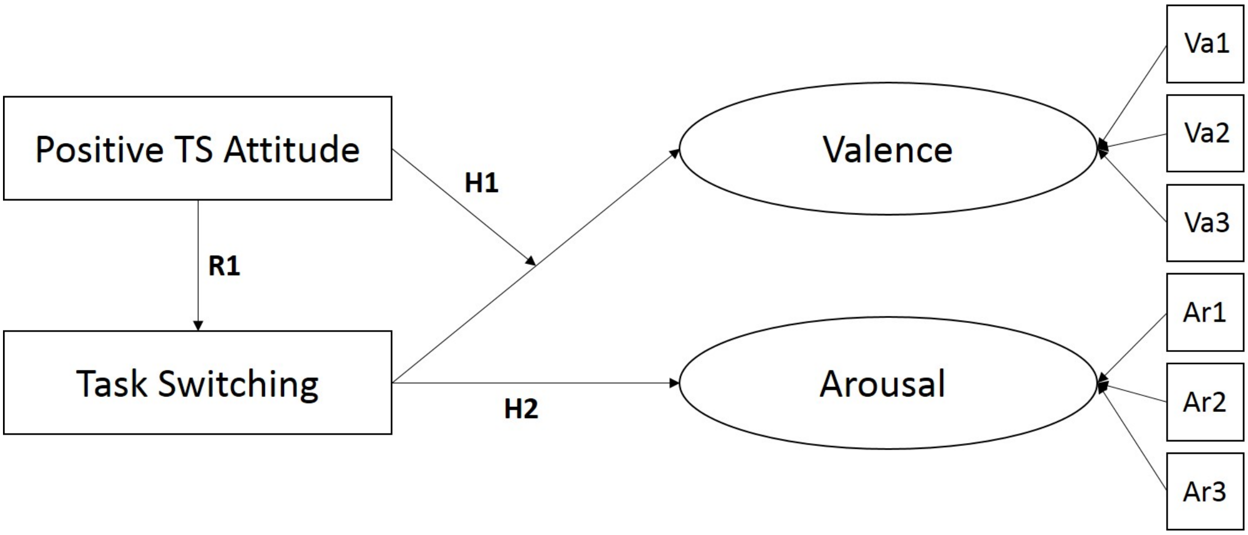
Arousal

Separating arousal from valence in media studies can be difficult (Lang et al., 1995). Like valence, the concept of emotional arousal is characterized by a dimension from high to low (Bolls et al., 2001). Individuals in a state of high arousal are stimulated, wide awake, and excited. A low state of arousal is identified as calm, sleepy, and unenthused. Unlike the valence dimension, arousal is primarily related to the defensive cognitive motivation (Lang & Bradley, 2010). This does not mean an experience is necessarily negative, but that while aroused, an individual pays closer attention to elements in the environment. While in a state of high arousal, a person can be enthusiastic, but this state is not necessarily pleasurable or unpleasurable. An optimal level of arousal triggered by an ideal balance of difficulty and fulfillment is also the basis of flow experiences (Csikszentmihalyi, 1990).

Arousal, which is associated with defensive motivation, is triggered by orienting stimuli, environmental signals that prompt an automatic attention response (Lang, 2006). For example, Galvis et al. (2010) used audio stimulus through an 80-decibel tone, the volume of a dial tone or alarm clock, to increase arousal during studies of random and predictable task-switching. As an automatic, biological response, the prevalence of the various dings, pings, flashes, and buzzes of media devices while task-switching should increase arousal. This response is predictable from any individual regardless of attitude toward task-switching. This relationship is tested through the second hypothesis. A visual summary of the predicted model is presented in Figure 1.

H2: As task-switching increases, arousal will increase regardless of the individual's attitudes toward task-switching.

Figure 1: Simplified hypothetical model.



EMA

An important limitation to much media multitasking research is the method of measuring media use and subsequent effects. Judd and Kennedy (2011) popularized media use measures via software that records every app usage or computer process. The measurement is highly precise on a single device but cannot yet measure the full scope of mediated activities that occur on multiple devices. In a laboratory environment, physiological measures of heartrate and skin conductance can be collected, but even the most modern sensors fail to capture accurate physiological data in natural settings for periods of time beyond a few hours (Labonte-LeMoyne et al., 2018; Thammasan et al., 2020). To capture effects of media use over the course of several days, psychological measures are the only viable option. Another method of media use measurement is cross-sectional survey data, as used by Ophir et al., (2009). Survey data allows for efficiently collected, large datasets measuring activity on several devices and psychological measures, but there is evidence to suggest limited ability to accurately recall mediated activities (Block, 1990; Block & Zakay, 1996; Scharkow, 2016; Sucala et al., 2010; Xu & David, 2018).

A middle ground between these two methods is ecological momentary assessments (EMA). The term EMA was coined by Stone and Shiffman (1994) to encompass a variety of real-time data gathering methods used in the fields of health and medicine. These strategies included written diaries and experience sampling (Shiffman et al., 2008), but EMA has been rejuvenated with the widespread diffusion of web-connected, mobile devices. Digital EMA methods are accessible through smartphones with a text message-like reminder prompting study participants to complete one-minute surveys. This method provides a level of precise measurement unavailable through cross-sectional surveys by reducing the amount of time between mediated activity and recall. EMA also gathers data unobtrusively during natural media use environments, without privacy-invading collection of every piece of content and click. Finally, EMA measures responses longitudinally, which allows for situational differences and affective responses to be recorded (Moskowitz & Young, 2006).

Using EMA, a respondent can, for example, provide precise information about their media consumption and emotional response after their morning routine, during lunch, while working in the afternoon, and while relaxing in the evening through a series of one-minute surveys. This approach is similar to Deng et al.'s (2018). They find EMA methods of smartphone behaviors and behaviors collected through tracking software can still differ. However, EMA does allow for real-time measurements of attitudes about media use, which has not yet been done.

Although EMA provides opportunities to measure media use, the method also presents a unique set of challenges. Primarily, EMA constricts the level of detail gathered during each measurement. This was potentially problematic in both the media use and emotional state measurements. The detailed media-use measurements used in longer surveys or diary methods (Czerwinski et al., 2004; Spink, 2003; Jacobsen & Forste, 2011) were not possible, but we utilized the condensed format to focus on the objective measure of number of task switches which Benbunan-Fich et al. (2011) suggest is an accurate measure of how individuals shift focus among "ongoing but unrelated tasks" (p. 7:16). However, others have shown even these methods vary from tracking-based methods (Deng et al., 2018). Also, the brevity of each survey limited the measurement of valence and arousal to two three-item indices. This shortened instrument is not problematic because of the acceptable alpha values and because we combined the EMA method with an initial full-length questionnaire to gather baseline attitudes. In relation to the research question and hypotheses, this provides a promising approach to analyze attitudinal effects of task-switching behaviors.

Methods

Procedure

To address the research question and hypotheses, a two-level structural regression model was tested using data from a pretest survey and EMAs administered through a mobile application. To increase the sample size, data was gathered twice, once in the spring of 2014 and once again in fall 2015. While the measures remained the same from spring to fall, the number of days and EMA collections were reduced to avoid participant fatigue in the second data collection. Responses and data quality did not differ significantly between the two data collections, so the datasets were combined before analysis.

After signing up for the experiment, subjects were given the opportunity to select a range of days to complete the design. On the first day, the subject received an email with a link to the pretest, which was hosted online. At the end of the pretest, they were asked to select whether they would like to complete the EMA portion on an iPhone mobile application or as a series of short online surveys sent to their email inbox.

The EMA portion of the design began the following day. Starting at 10 a.m., the subject began to receive notifications to fill out EMA surveys every two hours. During the spring data collection period, they received five surveys per day for three days. During the fall data collection period, they received seven surveys per day for two days to reduce the overall length of the study. As such, subjects could complete up to 15 or 14 EMA surveys in total depending on which session they were in. Subjects were asked to not fill out multiple surveys in a row if they missed a survey time, but instead to wait until the next notification so there was no overlap in survey results.

Each EMA survey consisted of 15 questions and could be completed in less than three minutes. These questions attempted to capture switching behaviors and mood in the previous hour. Participants using the mobile app were identified by their unique login number, whereas email users had one additional question asking for their email as identification. This information was used to link pretest results to EMA data and was recoded immediately after to preserve user anonymity.

The Mobile Application

The application used to administer the EMA surveys was Real Time Research (RTR) developed by Telybnova Research. It is a free application for iPhone users on iOS7 and higher. When subjects selected the mobile option, the researchers created a unique user ID number and password for them. These credentials, along with a link to the app and instructions, were sent to the subject the evening before the EMA portion of the design began. Within the RTR administration panel the researchers could set notification times for the EMA surveys. Users were encouraged to enable push notifications on their device so that each time the survey went live the student would get an alert. After completion of the experiment, the results from the EMA were exported by RTR into an Excel spreadsheet for transference into statistical software.

Sample

Subjects were recruited for the study through a college-wide research participation pool. Those who completed each portion of the design received extra credit in communication courses as an incentive. Being that multitasking is ubiquitous in the college lifestyle and diffusion of smart phones is high (91% in this study) among college students, the sample was deemed appropriate.

Between the two periods of the experiment, 289 subjects completed the pretest. Of those, 196 (68%) owned an iPhone capable of running the mobile application, with the remaining being offered the email option. Some subjects opted out of the study at this time, leaving 202 in the EMA portion of the test. By the end of the EMA design, and after data cleaning to remove accidental submissions and non-linked entries, 162 subjects remained for analysis, meaning there was a 56% total completion rate, but an 80% completion rate for the EMA portion of the study. This retention falls well within the acceptable range for diary response methods (Green et al., 2006). There were 1628 complete EMA responses from these individuals, meaning an average of just more than 10 completed per subject. More than half the sample came from mobile application users (n = 86), who were responsible for 904 EMA responses, compared to 76 email users, who completed 724 EMA surveys. This difference between groups was not statistically significant.

Women made up approximately three quarters of the sample (n = 121). The distribution of participants across years in school was nearly equal, with 38 first-year students, 44 sophomores, 38 juniors, and 42 seniors. The sample was predominantly Caucasian (58%), with other subjects identifying as Asian (15%), Hispanic (8.4%), and African American (7.5%). About half (50.7%) of participants were single, with the other half being married (1.3%) or in relationship (34.4%). Only six subjects were older than 23.

Variables

Task-Switching

Task-switching was operationalized as a single manifest variable in the EMA surveys. Subjects were asked “In the past hour, how frequently did you switch between tasks?” on a seven-point scale. Anchors were “not at all” (1) to “very frequently” (7) (M = 3.47, SD = 1.73).

Positive Attitudes toward Task-Switching

Measured during the pretest survey, this index of items sought to determine the extent to which subjects had positive attitudes toward task-switching behaviors. Three parcels with six items each were used to tease out preference for multitasking “I would rather switch back and forth between several tasks,” enjoyment during multitasking “I find task-switching to be entertaining,” and perceived productivity of task-switching “I can get more work done when task-switching." This scale was collapsed into a single manifest predictor (M = 3.64, SD = .856, α = .860).

Valence

During each EMA survey, subjects were asked three questions about their current emotional valence based upon a scale by Bradley and Lang (1994). These questions asked, on a seven-point scale, how much they agreed or disagreed that in the past hour they were: happy (M = 4.71, SD = 1.46), pleased (M = 4.65, SD = 1.47), and content (M = 4.82, SD = 1.49) (α = .913).

Arousal

During each EMA survey, subjects were asked three questions about their current state of arousal based upon a scale by Bradley and Lang (1994). These questions asked, on a seven-point scale, how much they agreed or disagreed that in the past hour they were: stimulated (M = 4.08, SD =.55), excited (M = 3.59, SD = 1.56), and wide awake (M = 3.96, SD = 1.67). (α = .725)

Results

Multilevel Structural Equation Model

In order to explore H1, H2, and RQ1, a multilevel structural equation model was fit to the data. The study employed a within-participant repeated measures design. As such, the responses for any participant are dependent on that participant's other responses, violating the assumption of independence. To account for this, we specified a multilevel structural regression model that clustered the data by participant. The 1628 responses were clustered into 162 groups, one for each participant. For each participant, there was an average of 10 observations which each represented one completed EMA. According to Maas and Hox (2006), multilevel models benefit from larger numbers of groups and more observations per group, however, simulation studies show that at least 30 groups and at least 5 observations per group are sufficient to avoid bias in the estimation of parameters and variances. This data meets these recommendations. The model was based on the literature to reflect the interaction of positive attitudes toward task-switching and task-switching occurrence on valence, and the direct influence of task-switching occurrence on arousal. This model, along with indications of free parameters to be estimated by the data, is presented in Figure 2.

Description of the Data

Prior to model testing, the normality of the data was considered. All the variables in the proposed model had relatively normal distributions, with skewness being no larger than .269 in any case and kurtosis maxing out at .896. The Shapiro-Wilk test for normality was significant, however, the values were fairly close to 1, and the test is often influenced by the presence of a large sample. As such, a visual test of q-q plots was employed and found that the data was acceptably within the range of normality. All values, range 1-7, were considered to be continuous for the purposes of evaluation.

The correlation matrix (see Table 1) was used to consider relationships between variables to identify any possible problematic paths or relationships between variables. The correlation between the outcome variables suggests, as put forth in the model, that valence and arousal must be allowed to correlate. Only one correlation was particularly high in the matrix and being that it was two manifest variables that load on the same latent concept, this correlation is not surprising.

Table 1. Correlation matrix

	Switch	Val1	Val2	Val3	Ar1	Ar2	Ar3	Pos At.
Switch	-	.179*	.181*	.168*	.087	.170*	.138*	.026
Val1		-	.851*	.766*	.380*	.525*	.309*	.016
Val2			-	.805*	.394*	.527*	.280*	.031
Val3				-	.405*	.482*	.267*	.048
Ar1					-	.569*	.435*	.009
Ar2						-	.499*	-.003
Ar3							-	-.026

*Indicates a significant correlation at p<.01

The model estimation with clustering by participant to account for non-independent observations was completed using the COMPLEX command in Mplus, which is the appropriate specification for nested or clustered data (Muthén & Muthén, 2017). Missing data was dealt with prior to model fitting using listwise deletion. This method was deemed appropriate because only four cases in the EMA had missing data.

Measurement Model

Before using the multilevel structural regression model for hypothesis testing, it was re-specified as a measurement model with correlations among factors rather than causal paths. The measurement model can be seen visually in Figure 3.

The fit statistics indicated good fit for the measurement model using both relative and global fit measures: ($\chi^2(20) = 35.748$, $p < .05$; CFI = .995; RMSEA = .023, CI: .010 - .034). Path coefficients between factors were generally significant, with the exceptions being the paths between positive attitudes toward task-switching and arousal and positive attitudes with task switching. Since the measurement model was successful, the structural portion of the model was reintroduced for hypothesis testing.

Figure 2: Theoretical model.

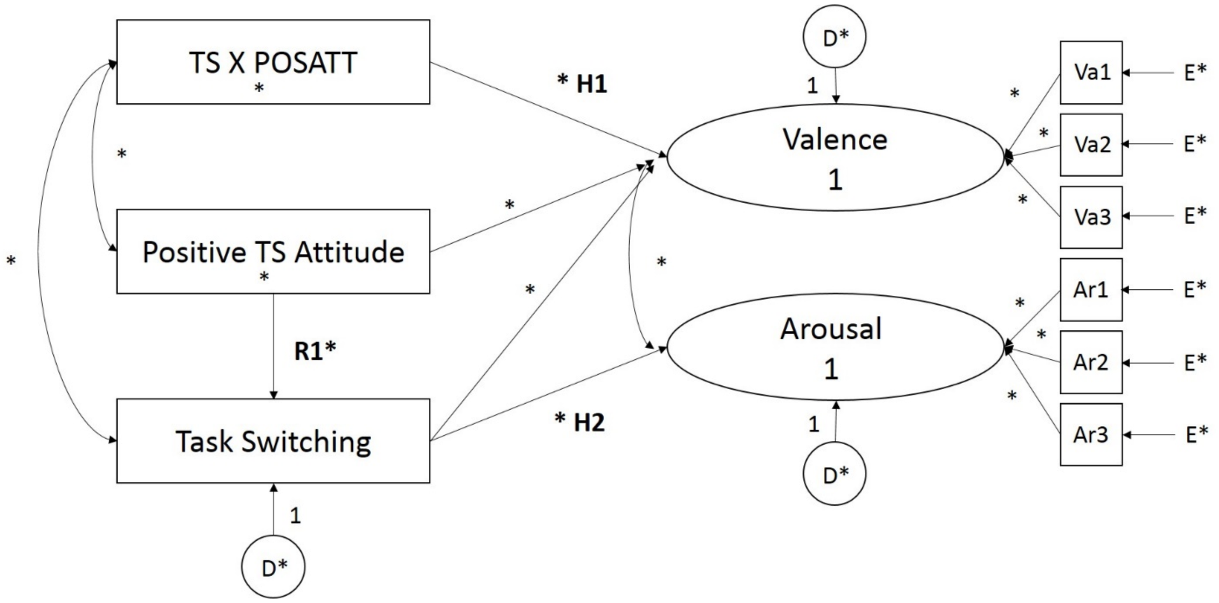
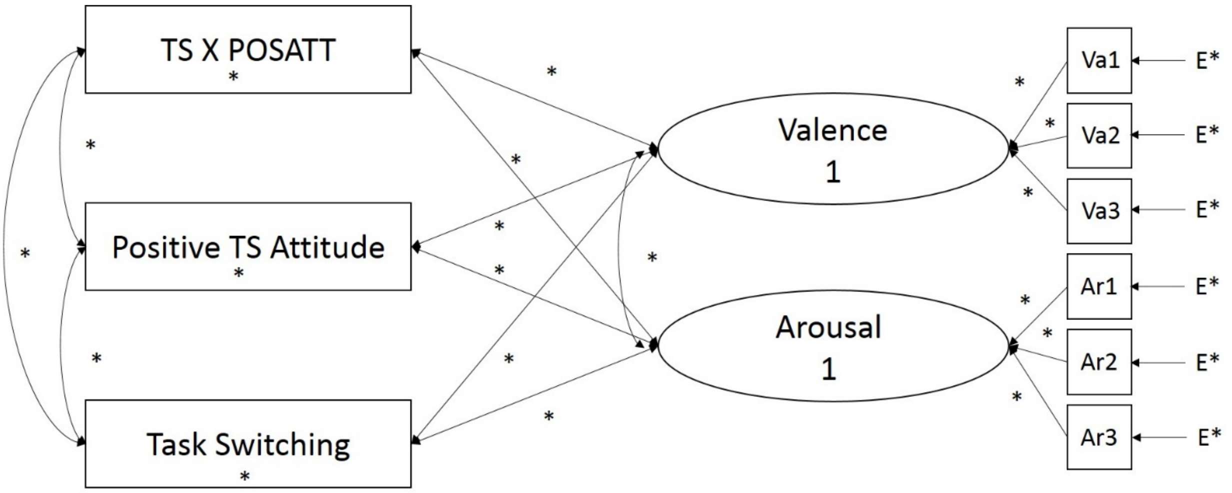


Figure 3: Measurement model.



Structural Regression Model Fit and Parameter Estimates

Similar to the measurement model, fit statistics for the theoretical model indicated good fit using both relative and global fit measures: (χ^2 (22) = 34.327, *p*< .05; CFI = .996; RMSEA = .019, CI: .003 - .031).

Parameter estimates in the final model can be seen in Figure 4. The RQ1 path was not significant with a standardized parameter estimate of .026. In other words, higher levels of positive attitudes toward task-switching did not result in significantly higher levels of task-switching. The H1 path, which was the moderating effect of positive attitudes toward task switching on the path from task-switching to valence, was found to be significant with a standardized parameter estimate of .268. This means that as task-switching increases, valence will either significantly increase if the person has positive attitudes toward task-switching or will significantly decrease if the person has negative attitudes toward task-switching. This can be seen visually in the graph in Figure 5. Additionally, the H2 path between task-switching and arousal was found to be significant with a standardized parameter estimate of .189. In other words, a one standard deviation increase on task-switching resulted in a .189 standard deviation increase in arousal. The absence of the interaction term did not result in a significant decrease in model fit and shows the relatively stable relationship between task-switching and arousal regardless of the interaction term. A simplified representation of these results can be found in Figure 6.

Figure 4: Theoretical model with parameter estimates.

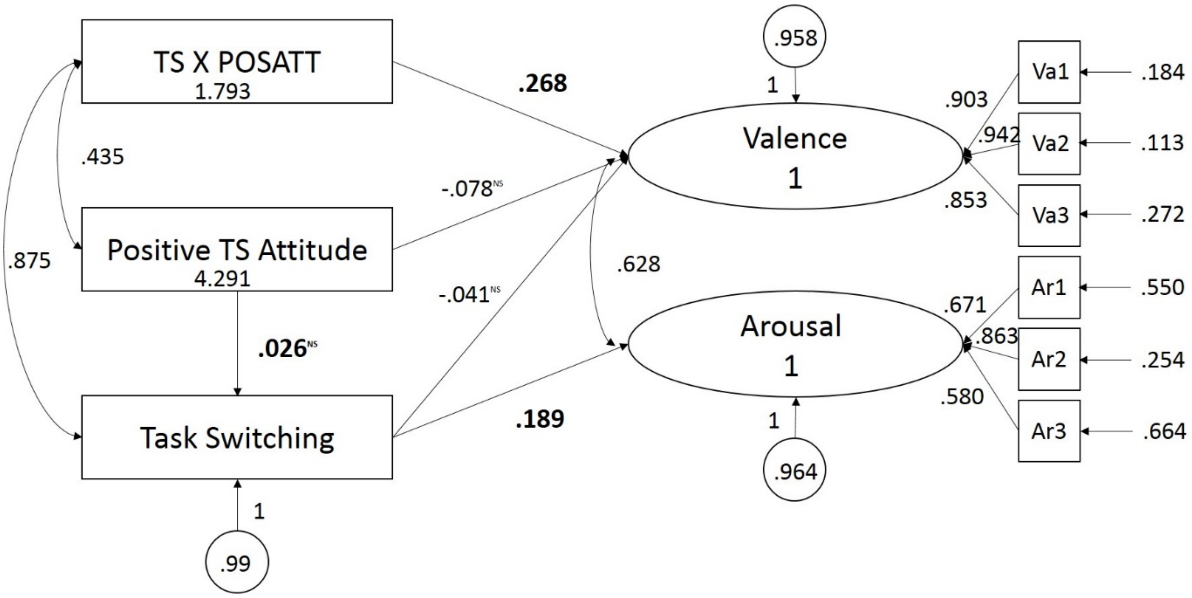


Figure 5: Graph of valence by task-switching for different levels of attitude

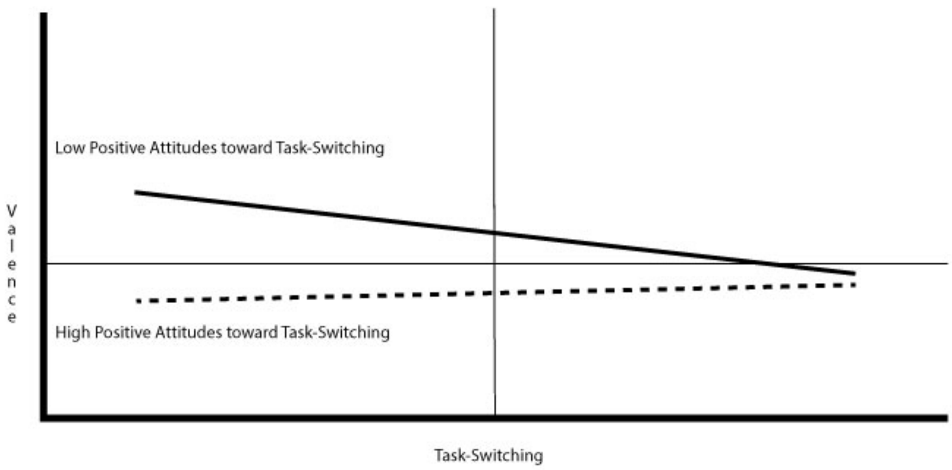
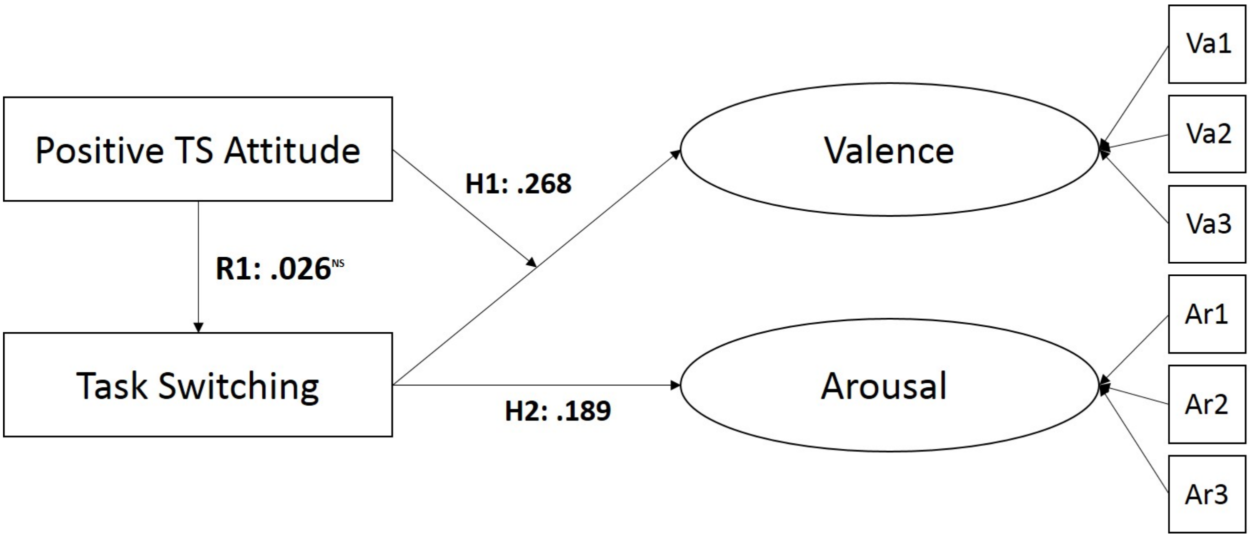


Figure 6: Simplified results model.



Discussion

The results of the structural equation model supported H1: Attitudes toward task-switching moderated the relationship between frequency of switches and valence. H2 was also supported: Frequency of switches was positively related to arousal. Finally, RQ1 was answered. There was no significant relationship between attitudes toward task-switching and the frequency of switches.

Implications

The findings from the structural equation model lead to some interesting considerations and questions. Consider first the nonsignificant path between positive attitudes toward task-switching and actual switching behaviors. This is perhaps the most surprising result. Theoretical models of behavior, such as the Theory of Planned Behavior, tend to show attitudes toward a behavior to be a significant predictor of a person completing the behavior. Task-switching, however, while recognizing the task switch control dimension of media multitasking (Want et al., 2015) presents a slightly different concept from other behaviors. In effect, traditional behavior-driven studies speak toward one single activity. Task-switching refers to any combination of other activities. As such, this study explores not whether the person wants to use social media, for example, but whether they want to put activities together with their social media use and whether this intention predicts behavior.

Still, the answer to RQ1 can be difficult to understand at first blush. A positive attitude toward clustering of activities would likely suggest an increase in the behavior. Consider, however, the earlier study discussed by Judd and Kennedy (2011) and the vast amount of task-switching that occurs in college students. Task-switching is becoming a more and more ubiquitous behavior. Likewise, students averaged more than seven activities in the previous hour during our study. Both would suggest that regardless of preference, people are not able to control their task-switches, whether it be due to societal pressure, as a goal-finishing strategy, a habitual pastime additive, or even just a way to cope with extremely busy mediated lives.

Likewise, there are times when task-switching is not an option. Due to the ecological nature of the data collection, some of the responses likely followed a classroom situation where task-switching is not allowed. Other respondents were filling out a survey upon waking, meaning that sleeping was their only activity in the previous hour. Other activities, such as driving, test-taking, and work could also present a time of relatively little task-switching despite a person’s preferences. In other words, sometimes people are forced to task-switch and sometimes they are not. Even though prior research shows task-switching can have positive outcomes, this lack of task switch control may frustrate user’s experiences.

We see this effect in the responses to the well-being measures of emotional valence and arousal. If people feel forced to task-switch (versus having control over their behaviors), their emotional response helps pinpoint why people might willingly choose to do one or the other in non-restrictive times such as leisure activities. The importance of the difference in valence and arousal becomes particularly marked in this case. A person loaded up with switching can be highly aroused but miserable. The same person could have little switching going on, leading to low arousal, but still enjoy themselves. In contrast, someone with high positive attitudes toward task-switching might relish the moments of rapid switching and become bored when forced to complete things in a more linear fashion.

With this difference in attitudes and lack of control better understood, the implications are far-reaching. We think well-being apps and redesigns of mobile software to track and flag high usage and minimize distractions will not necessarily improve emotional states. It is not only that people use mobile media frequently and need to be made aware of their behavior, but also that even those who know they do not enjoy task-switching lack the ability to control their behavior. More information on their behavior will likely not change this reality. Over the last 20 years, popular media and academic research have repeatedly said people cannot and should not multitask (Burkus, 2018; Hamilton, 2008). Yet if the last decade has shown anything, it is that guilting users for their high-frequency media behaviors does not reduce these actions. A more efficacious response may be to address the deeper alternative motivations that people balance that make task-switching worth its downsides like social connectedness, alleviating FoMO, and struggling with work-life balance.

These findings also point to a potential unintended negative effect of well-being promotion for users who are likely to track their media behaviors. Heavy multitaskers have been traditionally treated as synonymous with technology power-users (Kang & Shin, 2016), those who are most likely to customize their device settings. However, data suggest those who genuinely enjoy and, at least emotionally, benefit from task-switching should continue with the behavior. Extra reminders and barriers to their ideal experience may introduce an additional way to remove control from the user and ultimately turn a good experience to a bad one.

Returning to the grounding idea of task switch control, we think people know which experiences lead to the best overall outcomes for themselves and are able to balance multiple motivations beyond emotion and productivity. Even if attitude toward task-switching does not predict behavior, there are likely other motivations that are met by task-switching. The best way to improve well-being through communication technology may not be any omnibus solution but instead to build systems and devices that allow people to address and manage their competing motivations without having to manage paradoxes. For example, instead of removing or reducing notifications, anxiety over missing an important email could be managed by constant “all-clear” signals that don’t orient a user and increase arousal but instead eases stress while still providing information as soon as a person is able to attend to that task.

In addition to the implications above, one should consider what the ubiquity of task-switching and its relationship to valence mean for individuals who do not like to task-switch. Can people train themselves to enjoy task-switching more? And should they? With the explosion of platforms designed around the ease of task-switching, it seems that generational attitudes toward switching are coming from a habitual seed. Modality is important here. Smartphones, for example, offer a seamless transition between tasks that could perhaps mask the switch. People who dislike task-switching could be more able to complete it without the negative valence when staying on the same device – an undeniable cornerstone to the “all-in-one” paradigm for mobile device design.

Limitations

As with any study, there should be a consideration of the limitations of this piece from both a methodological and theoretical standpoint.

The former of these presents several challenges based around the task-switching construct. In short, it's difficult to measure. In this study there was no direct measurement of switches. Instead, participants reported their switches, or more accurately, recalled their perceived switches. Although the EMA design helps reduce memory recall issues for participants, it does not give us the chance to know for certain the number of switches because it was being held in a real-world setting. A lab study could solve this with eye-tracking software, but this step would reduce how applicable it would be to the real world. Indeed, even software used on a participant's personal laptop or phone would miss out on all the other types of task-switching, such as driving while on the phone, cooking while watching television, or even just the switching back and forth between the multiple devices. Measuring task-switching is difficult from a methodological perspective. However, the compromise of methodology discussed in the literature of this piece helps tease out that difficult operationalization.

Another difficulty is deciding what it means to "switch." Some of the examples above, such as driving while talking on the phone, do not involve a traditional switch. Rather, they seem to occur concurrently. This is similar to cross-modality or multitasking with low structural interference (Jeong & Hwang, 2015), such as writing an essay while listening to music. Additionally, researchers must ask when the threshold for a true switch has occurred. If a person stays on the Internet, but jumps between tabs, is it a switch? Further, what if they are still going toward the same goal, such as switching from one article for homework to another? This is less straightforward than a switch of media, such as computer to phone. As such, there needs to be some consideration of the strength of the switch. How much do we anticipate the switch and how much focus do we apply to each task? Further, can a surprising orienting response, such as a person reacting in fright to a banging door, be considered a task-switch? The brain changed its focus, but only due to a fight or flight reaction. How does this compare to a purposeful switch? As can be seen, there are several questions about the operationalization of what a task switch might be.

An additional limitation is our narrow definition of well-being as emotional or hedonic well-being and operationalization as positive emotional valence and arousal. Although positive emotions are an important aspect in theories of well-being like PERMA (Seligman, 2018) and Keyes' (2007) model of complete mental health, there are other aspects of well-being that we do not consider in this study. For example, in Ryff and Keyes' (1995) six-factor model, well-being is made up of self-acceptance, growth, purpose, environmental master, autonomy, and positive relations. Emotional well-being may be the result of these factors, but alone does not constitute complete well-being. Future studies could better situate task-switching's effects on emotional valence alongside these other dimensions.

From a more grounded statistical perspective there were a few other concerns to address. This analysis used a multilevel model by clustering the data by participant. Although 10 observations per cluster is acceptable according to Maas and Hox (2006), a greater number of observations (30 or more) would further reduce bias in the estimated variance of the parameters. Our model also assumed that a person's attitudes toward task-switching are a static construct, as it was measured only once during enrollment in the study, when in fact it might be dependent upon many other factors. In addition, the factor loadings on the arousal variable were lower than what would be considered ideal. Some other measure of the arousal construct may have made the results clearer. Finally, the number of participants limited the number of variables that could be explored and adding more control variables might have helped to tease out a clearer picture of why people are experiencing higher or lower valence and arousal. For example, the type of activities being task-switched could paint a picture of which activities are commonly paired and the purpose behind the pairings. It could be that the positive valence was experienced not because of the task-switching but rather whatever task was being completed.

Finally, we made the choice to explore self-report measures, in part, to avoid issues of user privacy and data tracking. We question claims that strong theoretical work can only be conducted through intrusive measures that collect more and more data in finer detail from individuals. We agree with Couldry and Mejias's (2018) critique of the "naturalization of data capture" in the technology industry and research fields. Nonetheless, self-report measures have been said to measure more about the beliefs of participants than their actual media behaviors (Scharkow, 2016). It is unclear whether theories of media use should prioritize actual task-switching or participant's subjective experiences of task switching.

Conclusion

The implications and limitations discussed above create ample opportunity for furthering the discussion on media multitasking and well-being. With the ubiquity of task-switching secured as a reality in this mediated society, understanding it from different perspectives is particularly important. We measured valence and arousal through psychological instruments due to the inability for modern sensors to track physiological measurements across multi-day time spans. Day-long or repeated lab-based assessments may be a logical extension to prior research and bolster these findings. In addition, well-being spans beyond emotional reactions and downstream constructs like personal growth or mental health would expand these findings. Similarly, a mix of lab and ecological studies need to be compared to see how much of our reactions to task-switching are based on forced switching versus what we choose of our own accord.

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