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Two-step Model of Media Multi-tasking Switch Behavior and its Performance

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Abstract

The current study aimed to develop a two-step model integrating Markov chains and exponential density functions to examine Media Multitasking (MM) switch behavior and its impact on performance. The research focused to explore the efficiency of MM switching and the factors influencing it, including task similarity, information flow, and behavioral response requirements. A quantitative approach was employed using data collected from a population of 1,722 university students with a mean age of 20.56 years. The study used stratified random sampling to ensure representative data. Furthermore, the Media Multitasking Index (MMI) questionnaire was adapted to assess weekly usage and simultaneous multitasking across ten media types. The model calibration demonstrated acceptable goodness-of-fit, with a Mean Absolute Percentage Error (MAPE) of 0.499. The key findings revealed that ease of task-switching is the most significant factor affecting MM performance, followed by information flow and behavioral response requirements. The most frequent MM scenario involved "listening to music", "LINE", "browsing information online", and "replying to email", highlighting the interplay of complementary media characteristics. These results provide a framework to understand MM behavior and its applications in business environments, with implications to improve efficiency and design adaptive strategies for media engagement.

Keywords: Markov chain, Media Multitasking (MM), switch behavior, working performance

Introduction

The Media Multitasking (MM) is a popular behavior in the digital world. Multiple researches have been conducted (Bang, 2022; Hwang & Jeong, 2021; Shin et al., 2020) on the motivation, working efficiency, and mind wondering in MM. Furthermore, MM may also be applied in e-business

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environment, such as impulse buying in on-line shopping, the formulation of online advertising strategies for consumers in an MM situation, as well as how advertising appeal differs under MM. The topic of working efficiency in MM or the performance of MM switch behavior is most frequency discussed when researches explore different variables of MM.

Related research (Le Roux et al., 2021; Shin et al., 2020; Wammes et al., 2019) also indicates that the efficiency of MM depends on the speed of task-switching. The ability of multitaskers to quickly switch between two tasks is crucial. Speed efficiency is not merely about the actual switching rate, however, it also focuses on the individual's ability to maintain focus and switch attention between two media contents. This ability is further influenced by the similarity between two tasks.

Baumgartner and Wiradhany (2022) determined that "the ease of task-switching," "the information flow," and "the behavioral response requirement" are key factors that influence the performance of MM. This is because the characteristics of MM involve high control over task-switching, typically using the same sensory modalities and not requiring behavioral responses. Consequently, MM, aside from cognitive resources and demands, occurs more frequently in task combinations that provide immediate emotional gratification. Thus, the closer the tasks are in nature, the easier and faster the switching, leading towards higher efficiency.

This study incorporated the Baumgartner and Wiradhany (2022)'s factors as influences on task-switching, using Markov chain probability transitions to describe the impact of task-switching and task similarity on MM efficiency. Previous research (Bang, 2022; Baumgartner & Wiradhany, 2022; Hwang & Jeong, 2021; Shin et al., 2020) on multitasking behavior from a probabilistic perspective is scarce. Ye et al. (2023) employed a hidden Markov model to derive several latent states influencing online store visits and purchasing behavior among media multitaskers. Unlike Ye et al. (2023), this study used a Markov chain to describe the MM task-switching process. For this purpose, task similarity/dissimilarity was incorporated and integrated into a joint probability density function to predict the MM efficiency.

The current research is organized in four parts. Firstly, the literature review is demonstrated. The literature about MM research, such as cognitive load theory, MM switch behaviors, and the impact factors of switch behaviors is introduced. Secondly, the model proposed includes Markov chain to portray the MM switch behaviors, the distance concept to describe the similarity between two MMs, and their probability distribution. Third part comprises the empirical data collection, which shows the descriptive data analysis and separation data for parameters estimation of this proposed model. The model calibration was also conducted to demonstrate the goodness-fit between real data and proposed model. Finally, the study was concluded. The model application in other business areas and suggestions for future research are shown in this part.

Literature Review

Past researches on MM mainly were conducted from the perspective of cognitive load (Bang, 2022; Ophir al., 2009; Sanbonmatsu et al., 2013; Shin et al., 2020; Wang et al., 2012). It was believed that multitasking behavior would cause cognitive functions to switch and process multiple different tasks at the same time, and the load may increase, resulting in reduced operational efficiency (Wang et al., 2012). It was determined that heavy media multitaskers perform poorly in task-switching (Ophir al., 2009) and are more susceptible to external interference when shuttling between different tasks (Bang, 2022; Sanbonmatsu et al., 2013; Shin et al., 2020). However, some studies have determined that more frequent participation in MM may lead towards higher perceived information utility (Chang, 2017; Hwang & Jeong, 2021). Habitual media multitaskers tend to focus on and process more information even when information is not directly relevant. People who frequently engage in MM have cognitive tendency to engage in and process more information from multiple media, which may lead towards higher perceived information utility (Chang, 2017; Hwang & Jeong, 2021). Some studies have found that when two consecutive sources are independent, individuals would perceive high information utility (Bang, 2022; Chang, 2017; Hwang & Jeong, 2021). Brasel and Gips (2011) explored MM situation from television to the Internet and found that individuals would obtain more information. This is because these information sources are mostly independent of each other. Individuals are more likely to think that the overall information utility is high and this higher perceived information utility may result in higher motivation to process subsequent messages.

Baumgartner and Wiradhany (2022) found that when MM occurs, these MM combinations are characterized by a high degree of control over task-switching. This is because these MM combinations usually use the same sensory mode and require no behavioral response. Thus, the working efficiency of MM, in addition to cognitive resources and demands, occurs more frequently in MM combinations that provide immediate emotional gratification. Therefore, the higher the proximity between the two tasks, the easier and faster the switching would be. The faster the switching speed, the better the working efficiency would be. Thus, MM is associated with the ability to prepare tasks faster, allowing for faster task-switching performance without compromising accuracy (Alzahabi et al., 2017).

According to Elbe et al. (2019) the focus on MM was used as a measure of task-switching effect. Their research results determined that higher levels of MM were related to lower switching costs of two attention-shifting tasks, indicating that heavy media multitaskers performed better on selected measures of task-switching. This is because frequent media multitaskers have developed required skills by switching between tasks. While high media multitaskers have multitasking switching capabilities and skills to be highly productive, they choose better method of MM task processing.

Related research (Baumgartner & Wiradhany, 2022) determined that the main factor affecting multitasking efficiency is the speed of task-switching. Tasks with similar properties may be switched faster and vice versa. The switching speed and similarity of properties are affected by the following factors:

1. The ease of task-switching
2. Information flow
3. Behavioral response requirement. These are introduced as follows:

The Ease of Task-switching

MM can be differentiated based on the degree of controllability that people have over switching between media activities. User's controllability is a characteristic of media. This allows media users to selectively focus on content (McMillan & Hwang, 2002) so that they may choose or change the pace and sequence of information presented by the media.

The Information Flow

Information flow refers to the type of information communication flow. Information can be transmitted in a static or dynamic transitory manner. For instance, written content is static, while music is dynamic and fluid. Therefore, static content may be paused and returned to continue processing later on. However, this cannot be done with dynamic, moment-to-moment information. In the MM state of dynamic instantaneous information, the user diverts attention from tasks. After moving up, the information would be lost and individual cannot easily return to continue processing immediately. Therefore, tasks with static content are more likely to form media multiplexing than tasks with dynamic momentary content. Since dynamic momentary information may easily lead to cognitive overload, the media multiplexing behavior of static information flow is better than that of media with dynamic momentary information flow. Thus, the static information flow can be easily chosen by media multitasker.

The Behavioral Response Requirement

The behavioral response requirement of MM for information processing would also affect the combination of MM tasks. For instance, interactive media, such as online games, social media, and telephone conversations are media activities that require behavioral responses (Ye et al., 2023). In contrast, watching television and listening to music are typically those media activities which are characterized by a more passive mode of reception. Therefore, media task combinations with low behavioral response requirements are more likely to be selected than combinations with high behavioral response requirements. Wang et al. (2015) compared a wider range of MM behaviors so that MM may be clearly represented as requiring behavioral responses to the characteristics of this variable, such as the MM combination of browsing the web. Chatting requires a high behavioral response and the behavior of browsing the web, while sending emails has relatively low behavioral response requirements. Baumgartner and Wiradhany (2022) conducted further tests, comparing a broader range of MM behaviors. They clearly defined MM as tasks that either require behavioral responses (e.g., browsing the internet while playing a game) or do not require behavioral responses (e.g., listening to music while watching TV).

The dynamic or static nature of content, referred to as information flow, also influences multitasking efficiency (Baumgartner & Wiradhany, 2022). For instance, written content is static, while music is dynamic. Static content can be paused and resumed later, whereas dynamic transitory information may be lost if the user's attention shifts away from the task, making it difficult to resume. Therefore, tasks with static content are more likely to form MM combinations, while dynamic transitory information may lead towards cognitive overloading. Consequently, MM involving static information flow is more frequently chosen over dynamic transitory information flow.

The Model

In this section, the derivation of the MM switch behavior performance model was conducted. Firstly, the characteristics of the Markov chain were be introduced, along with an explanation of why the MM switch behavior is described using a Markov chain. Based on this foundation, a probabilistic model was constructed to establish the relationship between the distance of different MM switch behaviors and their efficiency, thereby developing the MM switch behavior performance model.

MM Switch Behavior

It is considered as a Markov chain state where people switch from one media to another. If a "dual screen" MM is considered (which is a MM switch behavior between two media), the distance d_{ij} is from media i to media j. The attributes which influence the performance effect from media i to media j are (X, Y)defined as,

$$d_{ij} = p_{ij}\left(\left|x_i - x_j\right| + \left|y_i - y_j\right|\right) \tag{1}$$

which demonstrates the probability p_{ij} multiplied with the distance calculation from attributes (x_i, y_i) to attributes $\left(x_j, y_j\right)$. The Markov matrix is

$$d^m = \begin{bmatrix} 0 & p_{21}(|x_2 - x_1| + |y_2 - y_1|) & \dots & p_{k1}(|x_k - x_1| + |y_k - y_1|) \\ p_{12}(|x_1 - x_2| + |y_1 - y_2|) & 0 & \dots & p_{k2}(|x_{k1} - x_2| + |y_k - y_2|) \\ \vdots & \vdots & \dots & \vdots \\ p_{1k}(|x_1 - x_k| + |y_1 - y_k|) & p_{2k}(|x_2 - x_k| + |y_2 - y_k|) & \cdots & 0 \end{bmatrix} = \begin{bmatrix} 0 & \cdots & p_{k1}(|x_k - x_1| + |y_k - y_1|) \\ \vdots & \ddots & \vdots \\ p_{1k}(|x_1 - x_k| + |y_1 - y_k|) & \cdots & 0 \end{bmatrix} \tag{2}$$

d^m is referred to as the one-step transition probability matrix, representing the probability of transitioning from one media state to another in a single step. If the MM switch behavior follows a Markov chain with k states, the probability of transitioning from MM1 to MM2 can be expressed accordingly. $p_{12} = P(Z_1 = 2|Z_0 = 1)$.

Performance of MM Switch Behavior

The current research defined MM performance as an efficiency of MM switch behavior. For instance, if two tasks of different media are similar, then the efficiency of MM switch behavior would be higher. The higher the efficiency of MM switch behavior is, the more the efficiency of MM performance. It presents the distance between two MM. d_{ij} is the distance from switching media i to media j. If d_{ij} is shorter, then the efficiency of MM performance would be higher. It is considered as d_{ij} from 0 to r. Thus, it is considered as d_{ij} following exponential distribution with parameter θ as,

$$f\left(d_{ij}|\theta\right) = \theta \mathrm{e}^{-\theta d_{ij}} \tag{3}$$

Based on Baumgartner and Wiradhany (2022), the efficiency of MM switch behavior is influenced by the ease of task-switching, information flow, and behavioral response requirement. It is considered $g(\theta)$ as,

$$\begin{aligned} g(\theta) &= [\alpha + \theta(\beta_1 e + \beta_2 h \\ &\qquad + \beta_3 b)]\left\{\int_0^k [\alpha + \theta(\beta_1 e + \beta_2 h + \beta_3 b)] d\theta\right\}^{-1} \\ &= [\alpha + \theta(\beta_1 e + \beta_2 h + \beta_3 b)]\{2k^3(\beta_1 e + \beta_2 h + \beta_3 b)\}^{-1} \\ &= 2k^{-3}[\alpha(\beta_1 e + \beta_2 h + \beta_3 b)^{-1} + \theta] \end{aligned} \tag{4}$$

in which e is the ease of task-switching, h is information flow, b is behavioral response requirement, and α is the constant, whereas β_1, β_2, β_3 are parameters. $g(\theta)$ is a probability density function (p.d.f.) and θ is from 0 to k.

Then, the joint density can be calculated with,

$$\begin{aligned} f\left(d_{ij}\right) &= \int_0^r f\left(d_{ij}|\theta\right) \cdot\ g(\theta)\, d\theta \\ &= \int_0^r \mathrm{e}^{-\theta d_{ij}} \cdot \{2k^{-3}[\alpha(\beta_1 e + \beta_2 h + \beta_3 b)^{-1} + \theta]\}\ d\theta \\ &= \int_0^r \mathrm{e}^{-\theta d_{ij}}\ [2k\alpha^{-3}(\beta_1 e + \beta_2 h + \beta_3 b)^{-1}] + 2k^{-3}\theta \mathrm{e}^{-\theta d_{ij}}\ d \end{aligned} \tag{5}$$

$$= e^{-rd_{ij}}\left(-d_{ij}\right)^{-1} \ \left[2k\alpha^{-3}(\beta_1 e + \beta_2 h + \beta_3 b)^{-1}\right] \\ + e^{-rd_{ij}}\left(-2d_{ij}\right)^{-1}\left(-\theta d_{ij} - 1\right)2k^{-3}$$

$$= e^{-rd_{ij}}\left(-d_{ij}\right)^{-1}\left\{\left[2k\alpha^{-3}(\beta_1 e + \beta_2 h + \beta_3 b)^{-1}\right] \\ + k^{-3}\left(-rd_{ij} - 1\right)\right\}$$

Acceding to equation, (1), $d_{ij} = p_{ij}\left(\left|x_i - x_j\right| + \left|y_i - y_j\right|\right)$, then equation (5) can be demonstrated as,

$$f\left(d_{ij}\right) \\ = e^{-rp_{ij}A_{ij}}\left(-p_{ij}A_{ij}\right)^{-1}\left\{\left[2k\alpha^{-3}(\beta_1 e + \beta_2 h + \beta_3 b)^{-1}\right] \\ + k^{-3}\left(-\theta p_{ij}A_{ij} - 1\right)\right\} \tag{6}$$

in which A_{ij} is $\left|x_i - x_j\right| + \left|y_i - y_j\right|$.

Methodology

Empirical Data Collection

Empirical data was collected from the university students who were surveyed to report their MM use behavior. This study collected data through a questionnaire survey to estimate model parameters and validate the model. Since the collected sample was not intended for inferential statistics to generalize to the population, nor for a broad understanding of specific groups' media multitasking habits, the survey targeted third-year undergraduate students from the business school at a university in Taiwan. Given that, university students are one of the primary groups engaged in MM, this data collection method is reasonably justified. The sample collection period was from March 20th to April 20th, 2024.

The total sample size comprised 1722 students. There were 895 (52%) males and 827 (48%) females. The mean age was 20.56 years. The mean of MM use in a week was about 48.32 hours. Furthermore, the maximum MM use comprised four types of media simultaneously. In the situation of using four types of media at the same time, that is, “listening to music”, “LINE”, “browsing information online”, and “replying to email” were most common.

The questionnaire was based on Ophir et al. (2009) and Murphy and Shin (2022). They proposed Media Multitasking Index (MMI) which was used to assess hours per week spent using 10 forms of media. This study adjusted them to ten types of media that were more relevant to the current situation. These 10 media included (1) Reading print media, (2) Watching TV, (3) Watching computer videos (For instance, YT or online albums including Netflix), (4) Listening to music (including podcasts), (5) LINE and other communication software/mobile text messages, (6) Online/mobile games, (7) Social media, (8) Browsing information online (including non-social media), (9) Replying to email, and (10) Using a computer/tablet offline work.

Then, the subjects were asked "how many hours is the total usage time per week for each of these 10 types? (Unit: hours)" and "when you are using this media as your main job (the ones in bold are the main media), how often you use other media at the same time?" with 4-point Likert scale from "most of the time (4)", "sometimes (3)", "seldom (2)", and "almost never (1)".

Results

Model Calculation

According to the empirical data analysis, there are 10 types of MM use. It can calculate the quantity of $\left|x_i - x_j\right| + \left|y_i - y_j\right|$ from media i to media j. For this case, $i=1,2,...,10$ and also $j=1,2,...,10$. It presents the matrix of "Media (1)" to "Media (10)" as shown in Table 1.

Based on the empirical data, the transformation can be calculated from media i to media j, demonstrating P_{ij}. The results are shown in Table 2.

According to the results of Table 1 and Table 2, distance (d_{ij}) can be calculated between media i to media j by equation (1). The results are shown in Table 3.

Table 1

Quantity of $|x_i - x_j| + |y_i - y_j|$ between MM

$\lvert x_i - x_j\rvert + \lvert y_i - y_j\rvert$	Media (1)	Media (2)	Media (3)	Media (4)	Media (5)	Media (6)	Media (7)	Media (8)	Media (9)	Media (10)
Media (1)	0									
Media (2)	0.334	0								
Media (3)	0.451	10.233	0							
Media (4)	0.107	11.567	12.567	0						
Media (5)	1.256	2.346	5.654	0.245	0					
Media (6)	9.223	11.234	13.879	10.879	8.998	0				
Media (7)	2.587	0.565	9.667	5.345	7.554	10.876	0			
Media (8)	0.344	2.667	9.998	1.212	0.235	11.877	1.254	0		
Media (9)	3.889	3.556	10.897	0.987	1.254	11.065	3.674	1.265	0	
Media (10)	0.271	3.244	13.468	0.221	1.765	8.798	3.778	0.654	1.254	0

Note. (1) Reading print media, (2) Watching TV, (3) Watching computer videos (For instance, YT or online albums including Neflix.), (4) Listening to music (including podcasts), (5) LINE and other communication software/mobile text messages, (6) Online games/mobile games, (7) Social media, (8) Browsing information online (including non-social media), (9)Replying to email, (10) Using a computer /tablet for offline work.

Table 2

Probability Transition (P_{ij}) in MM

P_{ij}	Media (1)	Media (2)	Media (3)	Media (4)	Media (5)	Media (6)	Media (7)	Media (8)	Media (9)	Media (10)
Media (1)	1									
Media (2)	0.8977	1								

P_{ij}	Media (1)	Media (2)	Media (3)	Media (4)	Media (5)	Media (6)	Media (7)	Media (8)	Media (9)	Media (10)
Media (3)	0.6533	0.0123	1							
Media (4)	0.9987	0.1400	0.0887	1						
Media (5)	0.9234	0.9845	0.5644	0.8874	1					
Media (6)	0.0254	0.5633	0.0233	0.0233	0.1122	1				
Media (7)	0.8765	0.8744	0.2322	0.6678	0.7765	0.1201	1			
Media (8)	0.7786	0.9321	0.4332	0.7877	0.8023	0.0233	0.7866	1		
Media (9)	0.9684	0.8254	0.5532	0.8977	0.6787	0.1034	0.4566	0.9789	1	
Media (10)	0.8876	0.8766	0.1002	0.9821	0.7855	0.1008	0.6987	0.9887	0.9675	1

Table 3

Distance (d_{ij}) between MM

d_{ij}	Media (1)	Media (2)	Media (3)	Media (4)	Media (5)	Media (6)	Media (7)	Media (8)	Media (9)	Media (10)
Media (1)	0									
Media (2)	0.300	0								
Media (3)	0.295	0.126	0							
Media (4)	0.107	1.619	1.115	0						
Media (5)	1.160	2.310	3.191	0.217	0					
Media (6)	0.234	6.328	0.323	0.253	1.010	0				
Media (7)	2.268	0.494	2.245	3.569	5.866	1.306	0			
Media (8)	0.268	2.486	4.331	0.955	0.189	0.277	0.986	0		
Media (9)	3.766	2.935	6.028	0.886	0.851	1.144	1.678	0.578	0	
Media (10)	0.241	2.844	1.349	0.217	1.386	0.887	2.640	0.457	1.213	0

Parameters Estimation

To use empirical data in order to estimate the parameters of the proposed model, half of the data (861 data) was used to make estimation. Results are shown in Table 4.

Table 4

Results of Parameters Estimation in the Proposed Model

α	β_1	β_2	β_3	k	h
0.235	2.388	0.997	0.554	4.002	2.344

Results showed that $\beta_1$was highest than β_2 and β_3. Based on equation (4), coefficient (β_1) was indicated to the ease of task-switching of MM. It means that this trait is the most important when exploring the influence of efficiency of MM switch behavior. The second and third important are information flow and behavioral response requirement, respectively.

Model Calibration

It uses another half of the data to make model calibration. This research used Mean Absolute Percentage Error (MAPE) to determine the goodness-fit between real data and proposed model. It may be demonstrated as,

$$\text{MAPE} = \frac{1}{n}\sum_{m=1}^{n}\frac{\left|D_m - \widehat{D_m}\right|}{D_m} \tag{3}$$

in which *n* is the total data size, *D* is the real data value, and $\widehat{D}$ is the forecast value. It uses half of the empirical data for model calibration to calculate MAPE as,

$$\text{MAPE} = \frac{1}{861}\sum_{m=1}^{861}\frac{\left|D_m - \widehat{D_m}\right|}{D_m} = 0.465$$

The result of MAPE was 0.499 which is smaller than 0.5. It demonstrated acceptable goodness-fit of the proposed model.

Conclusion

The current study combined Markov chain and probabilistic model to describe the MM switch behavior and its related working performance. This proposed model is called a two-step model. This is because it first uses the transforming probability to demonstrate the switch behavior from one media to another, then uses exponential density to predict the working performance by the important factors which influence the efficiency of MM switch behavior. Ye et al. (2023) also used a Markov chain to study MM. They employed a hidden Markov model to derive several latent states influencing online store visits and purchasing behavior among media multitaskers. The study identified four main states—efficiency, control, information, and habit—that explained the motivations of media multitaskers. When driven by control motivation, the probability of visiting an online store is highest. In the context of online store visits, the purchase conversion probability is highest under the control motivation state, followed by habit, efficiency, and information states. However, this study differs from Ye et al. (2023) as it evaluated MM efficiency based on task switching efficiency (that is, task similarity). It incorporated factors, such as the ease of task-switching, the information flow, and the behavioral response requirement as influences on task similarity.

The results confirmed that the degree of behavioral response requirement, the information flow, and the ease of task-switching would affect switch efficiency. It was also determined that the most common MM situations when individuals use more than two media include the combination of "listening to music", "LINE", "browsing information online", and "replying to email". The characteristic of this association once again confirmed the important of these three factors. These four simultaneous media characteristics are embedded in each other with the mutual effects of information flow, complementarity, and response frequency.

This study, from the perspective of media switch behavior, explored media switch efficiency and its working efficiency. In the future, other models may be used to investigate these relationships, such as U carve. Furthermore, other probability density may also be proposed to find the possible predictability.

Conflict of Interest

The author of the manuscript has no financial or non-financial conflict of interest in the subject matter or materials discussed in this manuscript.

Data Availability Statement

The data associated with this study will be provided by the corresponding author upon request.

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References

Alzahabi, R., Becker, M. W., & Hambrick, D. Z. (2017). Investigating the relationship between media multitasking and processes involved in task-switching. *Journal of Experimental Psychology: Human Perception and Performance*, *43*(11), 1872–1894. https://doi.org/10.1037/xhp0000412

Bang, H. (2022, November 11–12). *The effect of program genre on modes of media multitasking and ad processing* [Paper presentation]. Innovative Economic Symposium 2021 – New Trends in Business and Corporate Finance in COVID-19 Era. Seoul, South Korea.

Baumgartner, S. E., & Wiradhany, W. (2022). Not all media multitasking is the same: The frequency of media multitasking depends on cognitive and affective characteristics of media combinations. *Psychology of Popular Media*, *11*(1), 1–12. https://doi.org/10.1037/ppm0000338

Brasel, S. A., & Gips, J. (2011). Media multitasking behavior: Concurrent television and computer usage. *Cyberpsychology, Behavior, and Social Networking*, *14*(9), 259–275. https://doi.org/10.1089/cyber.2010.0350

Chang, Y. (2017). The influence of media multitasking on the impulse to buy: A moderated mediation model. *Computers in Human Behavior*, *70*, 60–66. https://doi.org/10.1016/j.chb.2016.12.071

Elbe, P., Sörman, D. E., Mellqvist, E., Brändström, J., & Ljungberg, K. J. (2019). Predicting attention-shifting abilities from self-reported media multitasking. *Psychonomic Bulletin & Review*, *26*, 1257–1266. https://doi.org/10.3758/s13423-018-01566-6

Hwang, Y., & Jeong, S. H. (2021). The role of user control in media multitasking effects. *Media Psychology*, *24*(1), 79–108. https://doi.org/10.1080/15213269.2019.1659152

Le Roux, D. B., Parry, D. A., Totolo, A., Iyawa, G., Holloway, J., Prenter, A., & Botha, L. (2021). Media multitasking, online vigilance, and academic performance among students in three Southern African countries. *Computers & Education*, *160*, 1–34. https://doi.org/10.1016/j.compedu.2020.104056

McMillan, J. S., & Hwang, J. S. (2002). Measures of perceived interactivity:

An exploration of the role of direction of communication, user control, and time in shaping perceptions of interactivity. *Journal of Advertising*, *31*(3), 29–42. https://doi.org/10.1080/00913367.2002.10673674

Murphy, K., & Shin, M. (2022). Frequent media multitasking is not associated with better cognitive flexibility. *Journal of Cognitive Psychology*, *34*(4), 516–528. https://doi.org/10.1080/20445911.2021.2002876

Ophir, E., Nass, C., & Wagner, A. D. (2009). Cognitive control in media multitaskers. *Proceedings of the National Academy of Sciences*, *106*(37), 15583–15587. https://doi.org/10.1073/pnas.0903620106

Sanbonmatsu, D., Strayer, D., Medeiros-Ward, N., & Watson, J. (2013). Who multi-tasks and why? Multitasking ability, perceived multitasking ability, impulsivity, and sensation seeking. *PLoS ONE*, *8*(1), Article e54402. https://doi.org/10.1371/journal.pone.0054402

Shin, M., Linke, A., & Kemps, E. (2020). Moderate amounts of media multitasking are associated with optimal task performance and minimal mind wandering. *Computers in Human Behavior*, *111*, 1–6. https://doi.org/10.1016/j.chb.2020.106422

Wammes, J. D., Ralph, B. C. W., Mills, C., Bosch, N., Duncan, T. L., & Smilek, D. (2019). Disengagement during lectures: Media multitasking and mind wandering in university classrooms. *Computers & Education*, *132*, 76–89. https://doi.org/10.1016/j.compedu.2018.12.007

Wang, Z., David, P., Srivastava, J., Powers, S., Brady, C., D'Angelo, J., & Moreland, J. (2012). Behavioral performance and visual attention in communication multitasking: A comparison between instant messaging and online voice chat. *Computers in Human Behavior*, *28*, 968–975. https://doi.org/10.1016/j.chb.2011.12.018

Wang, Z., Irwin, M., Cooper, C., & Srivastava, J. (2015). Multidimensions of media multitasking and adaptive media selection. *Human Communication Research*, *41*(1), 102–127. https://doi.org/10.1111/hcre.12042

Ye, M., Dahana, W. D., Baumann, C., & Li, X. (2023). When does media multitasking induce store visit and conversion? The influence of motivational factors. *Electronic Commerce Research and Applications*, *59*, 1–17. https://doi.org/10.1016/j.elerap.2023.101256