Computers in Human Behavior 63 (2016) 943–947

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Full length article

Media multitasking predicts video-recorded lecture learning performance through mind wandering tendencies

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A R T I C L E I N F O

Article history:
Received 27 July 2015
Received in revised form
5 May 2016
Accepted 16 June 2016
Available online 23 June 2016

Keywords:
Media multitasking
Mind wandering
Video-recorded lecture learning

A B S T R A C T

Media multitasking behaviors are on the rise globally. This phenomenon extends to academic settings, and has implications for education that is predicated on computer-assisted technology, which may be a source of distractibility for, especially, heavy media multitaskers. We hypothesized that habitual media multitasking correlates negatively with video-recorded lecture learning performance, with mind wandering mediating this association. Eighty-one participants from the National University of Singapore first completed a media multitasking survey (Loh & Kanai, 2014; Ophir et al., 2009). They then studied *Coursera* video-recorded lectures, during which their mind wandering tendencies were assessed using direct probes. Finally, participants attempted a test relating to what they have studied. Four regression models were built to analyse the data, and revealed evidence that supported the present hypothesis, even after we controlled for phenomenological variables relating to learning (i.e., anxiety, mental fatigue, and prior subject knowledge). Implications and future directions are discussed.

1. Introduction

Modern generations, owing to the ubiquity of portable and multi-functional Internet technologies, are engaging in unprecedented levels of media multitasking, which is broadly defined as the concurrent consumption of multiple media forms (Carrier, Cheever, Rosen, Benitez, & Chang, 2009; Rideout, Foehr, & Roberts, 2010). According to a recent review paper published in *The Neuroscientist* (Loh & Kanai, 2015), increased habitual media multitasking activity is associated with higher distractibility and decreased executive control. Specifically, individuals who engage in heavier media multitasking (HMMs) experience higher general distractibility (Waite, Levine, & Bowman, 2009) and more attention lapses in everyday life (Ralph, Thomson, Cheyne, & Smilek, 2014). Compared to light media-multitaskers (LMMs), HMMs are less able to exercise top-down control to suppress the processing of task-irrelevant information (Cain & Mitroff, 2011; Lui & Wong, 2012; Ophir et al., 2009). Loh and Kanai (2014) recently reported a biological link between media multitasking and executive control, which corroborated previous findings. Specifically, the study revealed that media multitasking negatively correlated with regional gray matter in the anterior cingulate cortex (ACC), a crucial node in the executive control network.

Pertinent to our research are studies which found media multitasking behaviors to be prevalent in such academic settings as lecture theatres and classrooms (Hembrooke & Gay, 2003; Jacobsen & Forste, 2011; Tindell & Bohlander, 2012) and associated with poorer learning (Wood et al., 2012) and academic grades (Clayson & Hayley, 2012). This fast growing body of work is particularly relevant in light of how the educational landscape is changing today. Education has traditionally revolved around a 'stand-and-deliver' pedagogical strategy, which is quickly becoming supplemented and increasingly substituted by newer models that have evolved in tandem with modern-day technological innovations and developments (see Khan, 2012 for a detailed discussion). Students can now receive education at the convenience and in the comfort of their homes, owing to the learning opportunities afforded by the Internet; online learning platforms, such as *Coursera*, *EdX*, and *Khan Academy*, host massive open online courses (MOOCs) that are accessible by learners globally.

Clearly, learners today enjoy access to a wide range of learning resources, and much flexibility to learn at their own preferred pace. However, it is important to note that successful online learning

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http://dx.doi.org/10.1016/j.chb.2016.06.030
0747-5632/

hinges heavily on the learner's ability to exert executive control – resist mind wandering and keep one's focus – whilst learning autonomously. According to McMillan, Kaufman, and Singer (2013), the concept of mind wandering relates to the "thoughts and images that arise when attention drifts away from external tasks and perceptual input toward a more private, internal stream of consciousness" (p. 1). Until only recently, the influence of mind wandering in educational settings – traditional classrooms as well as online learning environments – has been characterized as "underrecognized" (Smallwood, Fishman, & Schooler, 2007; see, also, Szpunar, Moulton, & Schacter, 2013b). This characterization has motivated both theoretical discussions and empirical investigations targeting possible linkages between mind wandering and education. Central to the present research are recent studies which have shown that mind wandering occurs frequently during video-recorded learning and is, in fact, associated with decreased learning of the educational materials presented (Risko, Buchanan, Medimorec, & Kingstone, 2013, 2012; Szpunar, Khan, & Schacter, 2013a). Increased mind wandering is, too, associated with higher general distractibility (Forster & Lavie, 2013) and a reduced ability to exert control over automatic thoughts (McVay and Kane, 2010). These findings, taken together, suggest that habitual media multitasking could predict the extent of success in video-recorded lecture learning, taking into account how much mind wandering had occurred during learning.

1.1. The present study

This research was conceived primarily to investigate the association between habitual media multitasking and video lecture lecture learning performance that is potentially mediated by learners' mind wandering tendencies. To test this hypothesis, we adopted the media multitasking index (MMI; Ophir, Nass, & Wagner, 2009) as a measure of habitual media multitasking activity. The MMI provided a reliable self-reported estimate of an individual's concurrent usage of different media types and had been used extensively across studies (e.g., Cain & Mitroff, 2011; Loh & Kanai, 2014; Yap & Lim, 2013). Participants viewed *Coursera* video-recorded lectures, and were subsequently tested on the lecture content as a way of measuring their learning performance.

Whereas previous media multitasking studies (e.g., Ralph et al., 2014) measured distractibility by collecting mind wandering self-reports, here we additionally tracked actual mind wandering events by administering direct probes at random time points (see Smallwood et al., 2007) during video lecture viewing (see Method section for details). We aim, in so doing, to make a side contribution by correlating, thereby validating, the self-report measures. Post-learning phenomenological ratings were recorded to provide further insights into participants' subjective video learning experiences. We expected habitual media multitasking, as evidenced by higher MMI scores, to be associated with poorer video learning test scores, with increased distractibility, as evidenced by participants' mind wandering tendencies, mediating this association. We also explored associations between our main variables (MMI scores, mind wandering scores, and test scores) and the post-learning phenomenological ratings.

2. Method

2.1. Participants

Eighty-one healthy undergraduate students [mean age = 20.93 (SD = 1.80); 49 were female] from the [National University of Singapore] participated in the current study. Forty-five participants received credits to fulfil an introductory psychology course requirement, whereas the other 36 participants received $10 cash reimbursement.

2.2. Materials

The modified Media Multitasking Questionnaire (Loh & Kanai, 2014) was adopted in its entirety. In this questionnaire, participants first reported the total number of hours per week they spent consuming 12 common media types: Print media, television, computer-based videos, music, mobile or telephone voice calls, online instant messaging, Short Messaging Service (SMS) messaging, web browsing, social networking sites, computer, video or mobile games and other computer-based applications. Next, via a matrix, the participants indicated the degree to which they would, while engaged in one media form as a primary activity, concurrently use other forms of media (1 "Never", 2 "A little of the time", 3 "Some of the time", or 4 "Most of the time"). Based on these responses, the media multitasking index (MMI) score for each participant was computed via the original mathematical formula documented in Ophir et al. (2009).

Participants viewed the video-recorded lectures on either a 24-inch color monitor of a Dell desktop computer or a 20-inch Fujitsu laptop computer. They were provided with standard Sony headphones; auditory output volume was adjusted to a comfortable listening level. The lecture videos were obtained from *Coursera*, a popular online learning platform, with permission from both the host provider and the respective course lecturers. The original video clips were edited and concatenated using iMovie software (Apple Inc.). Two different lecture videos were prepared: Video 1 was on geography, covering the topic of early Earth's sedimentary cycles and atmosphere, whereas Video 2 was on statistics, covering sampling and observational studies. The two lectures were controlled for both word count and duration (Video 1 contained 3028 words and lasted 18:28 min; Video 2 had 3063 words and spanned 18:15 min). 25 questions were developed for each video-recorded lecture video, along with answer keys and marking schemes for scoring participants' responses. Questions were designed to test the understanding of key concepts from the lectures (e.g., "What is the relation between a population and a sample?"), and responses were scored based on how accurate they were: one mark (correct), half a mark (partially correct), or zero marks (incorrect).

2.3. Procedure

Participants were, upon their arrival, provided with an overview of the study's proceedings. Informed written consent was obtained from all participants. Participants first filled out the media multitasking questionnaire at their own preferred pace. Following which, an important pre-lecture briefing was administered. Participants were told to learn the content of the video-recorded lecture as they normally would under a regular classroom setting. Each participant was assigned to an individual computer, and watched the lecture video whilst listening via headphones. This ensured that participants did not interact with or disturb one another. Participants were instructed not to take notes during the lecture.

Mind wandering was assessed via a direct-probing approach: At random points during the lecture, the experimenter rang a bell, which was to be taken literally as a question of whether their attention had strayed away from the lecture content at that moment in time (i.e., "Are you mind wandering?"). Upon hearing the bell, which was hidden from view, participants had to quickly write down a yes/no response on a blank piece of paper without pausing the lecture video. Participants were not told how many mind wandering probes to expect when, in fact, a total of four mind wandering probes would randomly occur at four specific times during the lecture. Mind wandering was taken as the proportion of ‘yes’ responses over the four time points in which they were prompted.

After the lecture viewing, participants were given a 2-min break, during which they played a Tetris video game developed by Tetris Holding. This was followed by a survey in which participants rated the following phenomenological items via a seven-point Likert scale (1 “Not at all” to 7 “Very much”): (I) how much they felt their minds had wandered during the lecture, (II) how much they felt their mind wandering had increased as the lecture progressed, (III) how anxious they were about the final test, (IV) how mentally taxing they found the experience of learning the lecture, (V) how interesting they found the lecture, (VI) how understandable they found the lecture content to be, (VII) how understandable they found the lecturer’s accent to be, and (VIII) how well they knew the subject matter prior to watching the video lecture. Participants were also asked to indicate whether they had watched the particular video lecture before.

The final test phase was designed to mimic actual examination settings: Participants completed the test at the same venue whilst sitting separately so that any interactions between them were prevented. They were allocated 15 min to answer all 25 questions. The questions were open-ended, and required responses in the form of short answers/sentences.

2.4. Statistical analyses

All statistical analyses were performed using SPSS statistical software (version 20.0; IBM Corp). Pearson’s pairwise correlations were performed to elucidate any relationships between MMI scores, mind wandering frequency, and video-recorded lecture learning test scores. We then explored associations between the main variables versus the demographic variables (i.e., age, gender) and post-learning phenomenological items.

We adhered to Baron and Kenny (1986)’s approach in testing whether mind wandering frequency mediated the association between MMI scores and video-recorded lecture learning performance. Under this approach, four regression models would be constructed: Model 1 predicting learning performance with MMI scores, Model 2 predicting mind wandering frequency with MMI scores, Model 3 predicting learning performance with mind wandering frequency and, finally, Model 4, a multiple regression model with both MMI and mind wandering frequency predicting learning performance. To infer successful mediation, Models 1, 2 and 3 would have to be significant. In Model 4, depending on whether MMI remains significant after controlling for mind wandering, mind wandering is then considered a partial, or full, mediator of the relationship between MMI and learning performance.

3. Results

The descriptive statistics of the main measures are summarized in Table 1. Participants’ MMI scores ranged from 1.00 to 6.96, with a mean score of 3.65 and a standard deviation (SD) of 1.48. These values were consistent with the mean MMI scores observed in other studies (e.g., 3.82 in Lui & Wong, 2012; 3.66 in Loh & Kanai, 2014; 4.38 in Ophir et al., 2009; 3.15 in Yap & Lim, 2013). The mean mind wandering frequency in the current study was approximately 32%, which fell within the range of 30%–40% observed in other studies examining mind wandering rates during video-recorded lecture learning (e.g., Lindquist & McLean, 2011; Schoen, 1970; Szpunar et al., 2013a). Participants scored, on the average, 10.4 marks (SD = 4.4) on the final test. Importantly, all participants indicated they had not previously seen the video lecture presented. The kurtosis and skewness values of the main variables all fell in the range of −2 to +2 (see Table 1), within which normality is assumed to hold (George & Mallery, 2010). This provided the justification to proceed with our main statistical procedures (i.e., correlational and multiple regression analyses).

We examined the correlations between MMI, mind wandering frequency, and test scores. As expected, both MMI and mind wandering frequency were negatively correlated with test scores ($r = -0.321$, $p = 0.003$ and $r = -0.409$, $p < 0.001$, respectively). Higher MMI scores were also associated with increased mind wandering frequencies ($r = 0.414$, $p < 0.001$). These findings provided preliminary support for our subsequent mediation analyses. Neither age nor gender correlated with the main variables. We then explored correlations between the main measures (MMI, mind wandering and test scores) and the post-learning phenomenological measures. Both accent and content comprehension were positively correlated with test scores ($r = 0.265$, $p = 0.017$ and $r = 0.439$, $p < 0.001$, respectively). This was unsurprising, since better intelligibility and comprehension would, all else being equal, enable better learning. Increased interest levels were associated with reduced mind wandering ($r = -0.391$, $p < 0.001$), lower MMI scores ($r = -0.270$, $p = 0.02$), and higher test scores ($r = 0.430$, $p < 0.001$). This was, again, unsurprising given that interest typically motivates learning, possibly evidenced by lower distractibility and better learning outcomes. Notably, self-perceived mind wandering levels and progression were highly positively correlated with actual mind wandering frequency ($r = 0.471$, $p < 0.001$ and $r = 0.357$, $p = 0.001$, respectively), and negatively related to test scores ($r = -0.502$ and $r = -0.426$, respectively; both $ps < 0.001$). The association between perceived and actual mind wandering provided evidence in support of the validity of self-reported measures of mind wandering. Critically, albeit expectedly, test scores were negatively correlated with anxiety ($r = -0.249$, $p = 0.025$) and mental fatigue ($r = -0.256$, $p = 0.021$), and positively correlated with prior knowledge of the subject ($r = 0.474$, $p < 0.001$). Based on these observations, we controlled for anxiety, mental fatigue levels and prior knowledge in our subsequent mediation regression analyses. Table 2 provides a summary of the correlational analyses performed.

Our main goal was to show that habitual media multitasking predicts video-recorded lecture learning test scores, taking into account mind wandering tendencies. Specifically, we tested if mind wandering frequency mediated the relationship between media multitasking and test scores. As detailed in Baron and Kenny (1986), we tested 4 regression models, as listed in Table 3. We then conducted another set of mediation analyses with the inclusion of

Table 1
Descriptive statistics of sample demographics and measures.

Variables	Mean (SD)	Range	Skewness	Kurtosis
Age (years)	20.9 (1.80)	18.0–25.0	0.363	−0.811
Gender (m = 1; f = 2)	1.60 (0.49)	–	−0.437	−1.855
MMI scores	3.65 (1.48)	1.00–6.96	0.324	−0.470
Mind wandering frequency	0.32 (0.30)	0–1	0.821	−0.139
Test scores	10.4 (4.44)	2.5–20.5	0.319	−0.725
Perceived MW	3.56 (1.52)	1–7	0.575	−0.628
Perceived MW progression	4.52 (1.67)	1–7	−0.377	−0.857
Anxiety	3.75 (1.68)	1–6	−0.380	−1.180
Mental fatigue	4.95 (1.44)	1–7	−0.736	0.001
Interest level	3.27 (1.62)	1–7	0.106	−1.051
Prior subject knowledge	3.00 (1.84)	1–7	0.159	−1.526
Content comprehension	3.95 (1.74)	1–7	−0.111	−1.022
Accent comprehension	4.99 (1.60)	2–7	−0.486	−0.914

$n = 81$ (49 were female).

possible confounding factors (anxiety, mental fatigue, and prior knowledge) as non-interest covariates. All of the four models, with and without covariates, significantly accounted for variance in the criterion variable (R^2 values ranged between 0.103 and 0.418, $p < 0.003$; see Table 3). Tests of multicollinearity indicated low levels of multicollinearity between all predictor variables (MMI: Tolerance = 0.789, VIF = 1.267; Mind wandering frequency: Tolerance = 0.808, VIF = 1.237; Anxiety: Tolerance = 0.788, VIF = 1.270; Mental fatigue: Tolerance = 0.698, VIF = 1.432; Prior knowledge: Tolerance = 0.860, VIF = 1.163). Overall, with and without covariates, mind wandering frequency emerged as a full mediator of the relationship between MMI and video-recorded lecture learning test scores: In Model 1, MMI significantly predicted test scores, with ($b = -0.259$, $p = 0.009$) and without ($b = -0.321$, $p = 0.003$) covariates. In Model 2, MMI significantly predicted mind wandering frequency, with ($b = 0.433$, $p < 0.001$) and without ($b = 0.414$, $p < 0.001$) covariates. In Model 3, mind wandering frequency significantly predicted test scores, with ($b = -0.399$, $p < 0.001$) and without ($b = -0.409$, $p < 0.001$) covariates. Finally, in Model 4, with and without covariates, MMI emerged as a non-significant predictor of test scores ($b = -0.105$, $p = 0.292$ and $b = -0.184$, $p = 0.104$, respectively), after controlling for mind wandering frequency which persisted as a strong predictor of test scores ($b = -0.355$, $p = 0.001$ and $b = -0.333$, $p = 0.004$, respectively). Altogether, this set of findings supported our hypothesis that habitual media multitasking (as evidenced by higher MMI scores) is associated with poorer video-recorded lecture learning test scores, with increased distractibility (as evidenced by participants' mind wandering tendencies) mediating this association.

4. Discussion

The relationship between habitual media multitasking and the degree of success in learning video-recorded lectures is mediated by the learner's mind wandering tendencies; this pattern of results holds after we controlled for anxiety, mental fatigue, and prior subject knowledge. Increased media multitasking activity has been found to predict, in some studies, greater mind wandering (Ralph et al., 2014) and, in other studies, poorer video learning outcomes (Lee, Lin, & Robertsona, 2012); mind wandering has also been shown to associate negatively with video learning (e.g., Szpunar et al., 2013a). Our research extends this literature by illuminating the exact pattern of interplay between media multitasking, mind wandering, and video-recorded lecture learning within a single study whilst controlling for extraneous variables relating to learning. It is worthwhile to note that whereas research examining links between media multitasking and learning has tended to focus on the role of *external* (e.g., technological) sources of distraction (see Carrier, Rosen, Cheever, & Lim, 2015 for a comprehensive review), the present study suggests that HMMs are in fact susceptible to general (internal) distractibility (even in the absence of any environmental triggers) whilst studying video-recorded lectures.

Why, then, might HMMs, as opposed to LMMs, be more susceptible to general distractibility and mind wandering during video-recorded learning? A prevailing theory is that habitual media-multitaskers, due to their constant need to concurrently cope with demands arising from multiple media forms, gravitate towards a mode of attentional control under which depth processing is forsaken in favour of breadth-wise processing (Lin, 2009). This theory has been supported by recent studies which found that HMMs were more proficient at integrating multisensory information (Lui & Wong, 2012) and more inclined to adopt a splitting, rather than unified, mode of visual focal attention (Yap & Lim, 2013). The interpretation is that HMMs, with a breadth-biased style of attention control, could be focusing on peripheral, irrelevant thoughts during video-recorded learning, leading to poorer processing of the lecture material. Furthermore, research has shown that the presence of technology promotes attentional shifts from the primary task as well as switching between tasks, thereby hampering task performance (Adler & Benbunan-Fich, 2013; Brasel & Gips, 2011; Rosen, Mark Carrier, & Cheever, 2013). As such, the nature of the computer-based environment in which video-recorded lecture learning takes place could, in itself, have contributed to the overall distractibility and mind wandering tendencies in HMMs.

Given the rising global trends in media multitasking and e-education, it is imperative to uncover factors that could mitigate the negative association between media multitasking – general distractibility – and video-recorded lecture learning. Loh and Kanai (2015), who reviewed studies that examined media multitasking and executive control, reported that HMMs consistently adopted a breadth-biased attentional control for tasks requiring reduced top-down intervention (e.g., visual target detection) but varied in their attentional strategies for tasks involving more top-down control (e.g., task-switching and inhibition of memory representations). This observation suggests that HMMs are, in fact, capable of relinquishing breadth-biased attentional control under certain task demands. But, more research is needed to elucidate the exact way in which HMMs, relative to LMMs, allocate their attention across specific kinds of executive tasks as well as any variables that may extenuate these decisions. Referencing the present study as an example, greater interest towards the study topic correlated with lower mind wandering and higher test scores. Future research could examine the role of interest cultivation in improving educational outcomes for, particularly, HMMs. Future studies could also examine the interplay between MMI and mind wandering tendencies in contexts of real-time online learning, in which learners would actually learn over a stipulated duration.

Finally, it is important to note that the current study reveals a link, rather than any causal relationship, between MMI scores, mind wandering tendencies, and video-recorded lecture learning performance. To establish any directionality between the three variables, a longitudinal study is necessary. Researchers could, for instance, implement training studies involving mindfulness-based cognitive therapy (MBCT; Segal, Teasdale, Williams, & Gemar, 2002) in which individuals learn to develop, over time, mindfulness in their everyday life. Recent evidence suggests that even a

Table 2
Pairwise Pearson's correlations between media multitasking index (MMI) scores, mind wandering (MW) frequency, test scores, and post-learning phenomenological ratings.

	MMI scores	MW frequency	Test scores
Main Variables			
MMI Scores	–	0.414***	−0.321**
MW frequency	0.414***	–	−0.409***
Test Scores	−0.321**	−0.409***	–
Demographic variables			
Age	*ns*	*ns*	*ns*
Gender	*ns*	*ns*	*ns*
Phenomenological ratings			
Perceived MW	0.284*	0.471***	−0.502***
Perceived MW progression	0.258*	0.357***	−0.426***
Anxiety	*ns*	*ns*	−0.249*
Mental fatigue	*ns*	*ns*	−0.256*
Interest level	−0.270*	−0.391***	0.430***
Prior subject knowledge	*ns*	*ns*	0.474***
Content comprehension	−0.258*	*ns*	0.439***
Accent comprehension	*ns*	*ns*	0.265*

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

Table 3
Regression models for testing mediation of mind wandering (MW) on relationship between MMI and video-recorded lecture learning performance.

Models and predictors	Without covariates			With covariates[a]		
	R^2	b	p	R^2	b	p
Model 1: MMI predicting test scores	0.103	–	0.003**	0.316	–	0.000***
MMI	–	−0.321	0.003**	–	−0.259	0.009**
Model 2: MMI predicting MW	0.171	–	0.000***	0.192	–	0.003**
MMI	–	0.414	0.000***		0.433	0.000***
Model 3: MW predicting test scores	0.167	–	0.000***	0.409	–	0.000***
Mind wandering	–	−0.409	0.000***		−0.399	0.000***
Model 4: MMI, MW predicting test scores	0.195	–	0.000***	0.418		0.000***
MMI	–	−0.184	0.104 (*ns*)		−0.105	0.292 (*ns*)
Mind wandering	–	−0.333	0.004**		−0.355	0.001**

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; R^2 = proportion of variance accounted for by model; b = standardized coefficient of predictor.
[a] Covariates included anxiety, mental fatigue, and prior knowledge about subject.

short-term mindfulness training course (spanning two weeks) can reduce mind wandering tendencies (Mrazek, Franklin, Phillips, Baird, & Schooler, 2013). There is reason to believe that long-term training can only enhance such a deliverable, and potentially enables HMMs to focus and fare yet better in an educational context, and beyond it.

Acknowledgements

This work was supported by a National University of Singapore Faculty of Arts and Social Sciences Heads and Deanery Research Support Scheme grant (R-581-000-150-133) awarded to LimSWH.

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