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Using time pressure and note-taking to prevent digital distraction behavior and enhance online search performance: Perspectives from the load theory of attention and cognitive control

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ABSTRACT

Digital distraction has become a chronic behavior problem for university students that interferes with their attention and learning within personalized learning environment. Applying a randomized control block trial with a counterbalanced experimental design, we investigated the effect of note-taking strategies and time pressure on students' task-irrelevant browsing behaviors and online search performance. Students were randomly assigned to a matrix note, conventional note, or note-free condition and then to one of the four experimental blocks, counterbalancing the order of online search topics and time pressure. Results of the study showed that 44 out of 60 participants (73.33%) conducted at least an irrelevant browsing. Students in the matrix note condition and those under high time pressure exhibited a lower task distraction rate. Moreover, students taking matrix notes demonstrated better online-search performance. Note-taking strategies and task distraction rate were significant predictors of participants' online search performance controlling for their prior knowledge. Study results are consistent with the load theory of attention and cognitive control and have implications to reduce student distraction and improve learning effectiveness.

1. Introduction

The Internet plays a crucial role in people's daily life in the digital era with its abundant affordances. For example, people rely on the Internet for various purposes, such as learning and information seeking as well as socializing and entertaining (Lee & Wu, 2013; Wu & Peng, 2017). Despite the many positive aspects of the Internet, the lack of a clear boundary between learning and entertaining frequently leads to media-related attention problems (Carrier, Rosen, Cheever, & Lim, 2015; Wu, 2015, 2017). Particularly, the rich information of the Internet and the diverse functions of media devices encourage users to no longer focus on one task at a time, resulting in so-called *media multitasking*. Thus, 62% of students reported using media unrelated to academic work when they were in class, studying, or doing homework (Jacobsen & Forste, 2011). Further, multitasking behavior negatively affects task performance and academic achievement (Adler & Benbunan-Fich, 2015; Junco, 2012; Wu, 2017) and makes it take longer to complete tasks (Bailey & Konstan, 2006; Bowman, Levine, Waite, & Gendron, 2010). These negative correlates of multitasking suggest that regulation of one's attention during online learning has become an important issue that needs careful investigation.

From an attention perspective, Chajut and Algom (2003) proposed that time pressure enhances task-relevant stimuli processing and prevents attention resources from being allocated to irrelevant tasks. Thus, an individual's selective attention may increase under time constraints. In addition to using time pressure as a prompt to prevent distraction, introducing a positive strategy during the learning task may have a significant impact on reducing online distraction and enhancing comprehension. For example, studies have found that taking notes helps learners concentrate and improves their attention in class (Kay & Lauricella, 2011).

Therefore, this study attempted to determine whether the effect of time pressure and use of a note-taking strategy can reduce distraction and enhance learning effectiveness in online search tasks using randomized control block trials with a counterbalanced repeated measure design. Specifically, we examined the following research questions:

RQ1 To what extent are university students distracted by things that are irrelevant to the task at hand, and what are they distracted by?
RQ2 Will university students' task irrelevant browsing behavior differ

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by levels of time pressure, note-taking strategies, and their interaction effects?

RQ3 Will university students' online search performance differ by levels of time pressure, note-taking strategies, and their interaction effects?

RQ4 What are the factors and variables that are predictive of university students' online search task performance?

2. Literature review

2.1. Selective attention, divided attention, and multitasking

Human beings have limited attention capacities so that they are not able to respond to and process all the environmental stimuli they encounter (Broadbent, 1958; Pashler, 1998). Attention failures occur when attention is shifted from the task at hand by distractors from the environment (i.e., a bottom-up process) or by internal thoughts (i.e., a top-down process), at the expense of failures in intended actions (Unsworth, McMillan, Brewer, & Spillers, 2012). For example, while studying, students may be attracted to social media notifications or may have lingering thoughts that friends might respond to their messages (Wu, 2017). That is, when faced with more than one source of information or task that needs processing, we are required to exert both selective attention and divided attention.

Selective attention is the ability to process only one specific stimulus while ignoring other stimuli, as in the early selection theory of attention (Broadbent, 1958). *Divided attention*, in turn, refers to the ability to divide attention resources and process multiple tasks simultaneously when faced with multiple stimuli (Kahneman, 1973).

Multitasking can be viewed as a kind of divided attention. Defined as attending to different sources of information and switching tasks across multiple media forms (Ophir, Nass, & Wagner, 2009), multitasking may or may not impair performance. That is, researchers have shown that levels of multitasking (number of switches) correlated with productivity in an inverted-U pattern but were associated with accuracy in a decreasing fashion in solving Sudoku problems with five secondary tasks (Adler & Benbunan-Fich, 2012). In a series of experiments, Pashler, Kang, and Ip (2013) required participants to be seated at a computer screen and read passages or listen to audiotaped lectures. Regardless of study form, the researchers found that as long as participants could control and pause their study pace and answer the interrupting opinion questions at the end of the task, their average comprehension scores did not differ from those of study participants who were doing the same task without interruptions. Further, Dindar and Akbulut (2016) found that college students obtained poorer retention scores in concurrent multitasking through online chatting and watching instructional videos. Nevertheless, watching different instructional videos or distraction videos in a sequential order did not sabotage retention. In a series of multitasking cognitive tasks, researchers showed that task hierarchy had a significant main effect on task performance (Hwang & Jeong, 2018). Specifically, participants were instructed to focus their attention primarily on one of the two cognitive tasks, a digit-symbol task (linking a symbol to a specific number) or a bell task (recognizing an audio or a visual bell). Regardless of task types, participants performed better in the primary task than in the secondary task. These studies clearly indicate that context, timing, and hierarchy of multitasking may influence students' performance.

From a goal-directed view, task-relevant stimuli deplete attention and reduce the allocation of attention to task-irrelevant stimuli. The mechanism, however, is not clear. Lavie, Hirst, de Fockert, and Viding (2004) presented the load theory of attention and cognitive control. This theory resolves the debate between early selection (Broadbent, 1958) and late selection of attention (Deutsch & Deutsch, 1963) to explain how the type and intensity of load affects an individual's resistance to distracting stimuli in selective attention.

Their theory includes two mechanisms: a perceptual selection mechanism and a cognitive control mechanism. For the first, consistent with the early selection view (Broadbent, 1958), increases in task-relevant perceptual load reduce distraction to irrelevant tasks due to insufficient perceptual capacities. In line with the late selection view (Deutsch & Deutsch, 1963), the second mechanism is associated with the frontal brain process of cognitive control, to inhibit behavior even when irrelevant stimuli are perceived. Within a closed learning environment, instructors can design their learning materials in a way that guides learners' attention and facilitates their learning (Richter, Scheiter, & Eitel, 2016). For example, Ozcelik, Arslan-Ari, and Cagiltay (2010) showed that coloring the term when it is narrated was beneficial for learning the mechanism of turbofan jet engines as evidenced by higher scores in the transfer and matching tests of the signaled group as well as their eye movement toward the colored term.

However, in the open online learning environment, learners perform online searches to do research or obtain information relevant with their respective aims. As a result, the intended searches are in conditions of low load with no planned designs (e.g. popup boxes, color coding, or notifications) to deplete their perceptual load and are specified by top-down attentional selection settings. Therefore, within the open online search paradigm, focused attention on the task relies primarily on active cognitive control in accordance with current processing priorities to reduce intrusions of irrelevant distractors.

We proposed two strategies to enhance active cognitive control of attention when learning online. Specifically, in performing online search tasks, we posited that note-taking may serve as a strategy to improve the top-down selection process and that task under time pressure may make active cognitive control of attention more salient to sort out priority events and prevent interruption from distractors. Therefore, in the present study, we investigated how different types and levels of note-taking and time pressure impacted students' learning and extent of task irrelevant browsing behaviors.

2.2. Note-taking and task performance

Note-taking may be regarded as a cognitive aid and an external store of the brain that enhances organization of information and prevents the brain from running out of cognitive resources (Lee, 2015, 2018; Lin, Lee, Wang, & Lin, 2016; Makany, Kemp, & Dror, 2009). Note-taking can take several forms, such as the conventional free notes, outline notes, matrix notes, and so on (Kiewra et al., 1991). Conventional notes are taken without a specific structure, whereas outline notes are taken in a hierarchical and list fashion. Finally, matrix notes are usually made in two-dimensional cross-tables, allowing subjects to be compared across categories (Kauffman & Kiewra, 2010). A number of studies have documented the positive effect of matrix notes, pointing to their advantages in terms of extracting important information, organizing information, and knowledge acquisition and comparison (Jairam & Kiewra, 2009, 2010; Kauffman & Kiewra, 2010; Kiewra et al., 1991).

Online search tasks require users to exert a great amount of higher-level cognitive ability, which involves complex information processing and decision making to integrate and access rich information gathered across multiple webpages (Lee & Wu, 2012, 2013; Wu, 2014). However, students' attention during online search may be greatly challenged by information irrelevant with their major task, resulting in media multitasking and poorer performance (May & Elder, 2018); thus, college instructors are encouraged to embrace the role in helping students stay focused besides delivering their instruction (Flanigan & Kiewra, 2018). Though note-taking may enhance students' active control of their attention (Kay & Lauricella, 2011), it may also be interrupted by multitasking. For example, a recent study showed that media multitasking interfered with the note-taking behavior and led to poorer learning performance; specifically, university students who texted while listening to a PowerPoint slide presentation took fewer quality notes than those who did not and that quality notes were positively related with learning performance (Waite, Lindberg, Ernst, Bowman, & Levine, 2018). Therefore, it may be important for students to have a structure for note-taking to help them prioritize their attention allocation and glean information during online search.

Based on the load theory of attention and cognitive control (Lavie et al., 2004), in the current study, we posited that matrix note-taking would help attention so as to preregister on stimuli that were relevant to the task and strengthen learners' perception of selecting and extracting relevant information for more complete notes. The two-dimensional format of matrix notes makes this strategy a productive tool for enhancing top-down selection and integration of information (Kauffman & Kiewra, 2010; Kiewra et al., 1997), whereby learners can quickly gain knowledge about one topic and compare information across many topics. In contrast, the conventional note strategy may not be able to increase active attention selection due to its lack of structure and external aids to quickly sort information into categories. Likewise, a note-free condition may expose learners to a low load state, making them easily attracted to task-irrelevant stimuli.

In this study, we adopted artificial food coloring and natural food coloring as our topics of two online-search tasks and examined the effects of conventional, matrix, and note-free strategies on the extent of distraction and online search performance among university students.

2.3. Time pressure and task performance

Time pressure may be conceptualized as the subjective feeling of a shortage of time. Svenson and Edland (1993) noted that "time constraint may lead to the experience of time pressure and more intense time pressure may increase the level of arousal and psychological stress" (p. 367). Studies have examined the effect of time pressure on task performance. For example, in a marketing research study, consumers increased the speed of information acquisition, filtered more information, and had more inter-brand saccades under high time pressure to make brand selection (Pieters & Warlop, 1999). Chajut and Algom (2003) demonstrated that selective attention using the Stroop test was enhanced under time pressure. In another study, participants enhanced their reading comprehension under mild time pressure through higher level of arousal of motivation and effort, but their performance deteriorated under severe time pressure (Walczyk, Kelly, Meche, & Braud, 1999). Further, examining participants' visuomotor task performance, researchers found that time pressure reduced time spent on completing a computer maze task but led to more behavioral errors; moreover, distinct patterns of electroencephalogram (EEG) in the theta, mu, and gamma bands along the midline were associated with time pressure during the task (Slobounov, Fukada, Simon, Rearick, & Ray, 2000). Similar findings were yielded in an event-related potential (ERP) study (Qi, Gao, & Liu, 2018), where participants in the time pressure group had faster response time in performing the arithmetic task and probe task (i.e., indicating the direction of an arrow) than their counterparts in the control group; nevertheless, the time pressure group had lower accuracy than those in the control group in the arithmetic task, but not in the probe task. The time pressure group also had larger fronto-central N1, N2, and less P3 waves when ERP was locked at the arrow. Consistent with the load theory of attention, these ERP indicators suggested that vigilance and sensory intake were augmented under stress (N1), leading to more active cognitive process (N2); however, it is also likely that fewer attention resources were allocated to process or evaluate the probe (P3) under time pressure.

It is possible that time pressure helps prioritize task-relevant information through the mechanism of active cognitive control of attention and avoidance of distractions from irrelevant stimuli (Lavie et al., 2004). Nevertheless, the accuracy of task performance may be compensated under time pressure. In the present study, therefore, we created experimental conditions that simulated the actual online search condition to test the assumption of time pressure on online open information search tasks; meanwhile, we provided note-taking strategies as external cognitive aids and examined their effects on students' online search performance.

3. Method

3.1. Participants

Participants were recruited through online advertisements from two universities in northern Taiwan. All of them had experiences to access the Internet and to perform online search tasks for course-related projects. Due to the nature of the online search topic (food coloring), we excluded participants majoring in food science as well as biology- or chemistry-related departments. Sixty undergraduate students participated in the study, including 14 freshmen, 17 sophomores, 14 juniors, and 15 seniors, among which 22 were males (36.67%). Thirty-six participants (60%) had a major in science or technology, while 24 participants (40%) had a major in humanity, art, or social sciences. Students received 10 USD as a token of appreciation (5 USD/hr) upon completion of the experiment.

3.2. Experimental design and procedure

The study employed randomized control block trials with a counterbalanced design to control for the confounding effect on the order of test conditions (time pressure) and task subjects (artificial or natural food coloring). Students provided oral consent to participate in the study and were notified that their onscreen behaviors would be recorded for analysis in an effort to understand the reading patterns among university students.

Each of the 60 undergraduate students received a two-stage random assignment using random number generators. At the first stage, each student was randomly assigned to a matrix note, conventional note, or note-free group with 20 participants in each group. Researchers explained the research procedure for 20 min. Students were told to perform online search tasks on food coloring in preparation for a research project. While listening to the task orientation, students could freely access the computer. The time set aside for task orientation (i.e., 20 min) was longer than the amount of time needed so that students had time to use the computer on their own to reflect their actual study habits.

Then, students were randomly assigned to one of four experimental blocks and started the experimental process. Each block was comprised of 15 randomly assigned participants with 5 individuals from each note-taking group to form a balanced experimental design. As shown in Fig. 1, each block consisted of a 5-min true-false (TF) pretest on students' prior knowledge, a 30- or 15-min online search task (dependent on the time pressure condition), a 5-min task load test, and a 10-min TF posttest test.

After a 10-min break, students performed another 15- or 30-min online search task (counterbalanced from the previous condition), a 5-min task load test, a 10-min TF posttest, and a 10-min constructed response (CR) test. As a result, each online-search task (artificial coloring or natural coloring) and each time pressure (high or low) was performed twice first and twice second. Therefore, the conditions and the order of online-search topics were counterbalanced to prevent a confounding effect.

3.3. Measure and instrument

3.3.1. Time pressure

Before setting the time pressure criteria, we recruited eight undergraduates to perform an online search on "artificial food coloring" or "natural food coloring" using the matrix note graphic organizer, followed by the TF posttest. The results showed that the average time to complete the task was 20.71 min, with a standard deviation of 6.73 min.

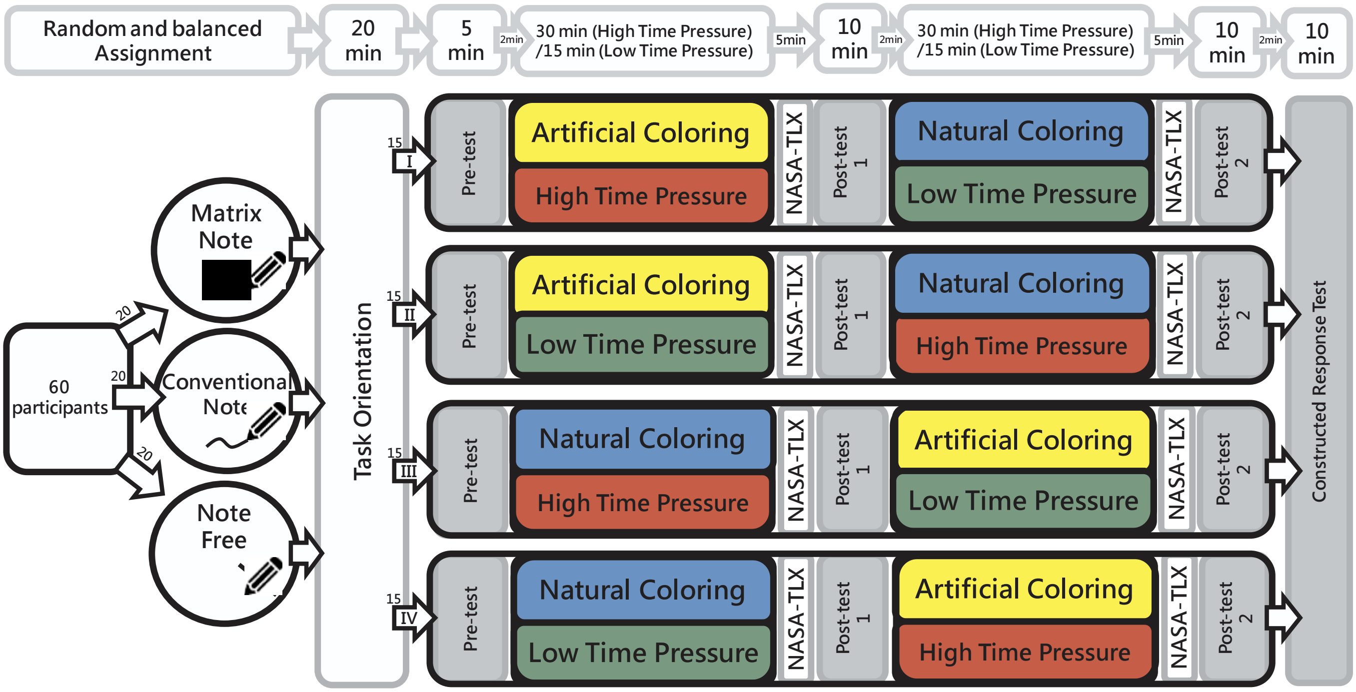

Fig. 1. The experimental procedure of the randomized control block trial with counterbalanced design.

We subsequently set the time limit for the high-pressure condition at 1 *SD* below the mean (20.71–6.73 ≈ 15mins) and the low-pressure condition at 1 *SD* above the mean (20.71 + 6.73 ≈ 30mins) (Weenig & Maarleveld, 2002). As a result, the students in the high-pressure condition were given 15 min to complete the task and the students in the low-pressure condition were given 30 min.

3.3.2. Task load

To verify the effect of the manipulation of time stress in the online reading task, the commonly used NASA-TLX (task load index) scale was applied to assess participants' perceived cognitive load, mental effort loading, and emotion (Hart & Staveland, 1988). The instrument includes six dimensions measured on a 5-point Likert scale (1 *lowest perception* to 5 *highest perception*), including mental demand, physical demand, temporal demand, performance, effort, and frustration. Only the "temporal demand" (How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred?) and "frustration" (How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?) items were utilized in this study to check the manipulation of time stress. The construct validity of NASA-TLX has been accumulated based on interrelationships from numerous studies, showing good generalizability (see Hart, 2006 for a review). In this study, we tested the construct validity of NASA-TLX with empirical data using multiple sources of evidence (Messick, 1987; Sireci, 2007). To do so, we calculated correlations among temporal demand, frustration, and irrelevant browsing measures. Scores of the temporal demand and frustration are positively correlated with a correlation coefficient of 0.302 ($p < .001$), exhibiting evidence of discriminant validity. Meanwhile, criterion validity was found as participants reporting higher temporal demand or more frustration also performed less irrelevant browsing behaviors across all conditions (*rs* ranging from −0.19 to −0.37, $p < .05$).

3.3.3. Note-taking strategy

To investigate the effect of note-taking strategy on students' level of distraction and performance, we included a matrix note, conventional note, and a note-free condition. Conventional notes were used as a baseline (Kauffman, 2004) in addition to a note-free control condition. The matrix notes were designed like a graphic organizer, with topic in the column (artificial or natural food coloring) and categories in the rows (general information, advantages, and disadvantages). Participants in the matrix note condition were given the pre-outlined matrix note for them to take note. All participants needed to generate their own keywords for the online search task.

3.3.4. T/F test items and CR item

Before creating the test items, we used keywords such as "food coloring," "natural food coloring," "artificial food coloring," and "food coloring pros and cons" in Chinese to search the web using the Google search engine. The test materials were created based on the non-controversial, declarative, and informative contents returned from the first three most relevant pages of search queries. The materials were reviewed and edited for their adequacy by a content-area expert. Two sets of 15 True/False (T/F) items were developed for natural food coloring and artificial food coloring, respectively, as the posttests. The pretest consisted of eight TF items covering both artificial and natural food coloring. Sample test items were "Artificial food colorings were originally manufactured from coal tar, which comes from coal (True)," and "Artificial food dyes are added simply for their color to make foods appealing and serve no health purpose whatsoever (True).

The CR item asked students, "If you were a hot pot restaurant owner, would you use food coloring? What kind of food coloring would you use? Please provide the reasons for your decision and how you would use the food coloring." The responses were rated in terms of position-taking, reasonable explanations for the food coloring decision, and correct use of food coloring. Position-taking was coded 1 for students who chose natural or artificial coloring and 0 for those who did not take a position. Scores for reasonable explanations and correct use were determined by the sum of every reasonable explanation or correct use given. The range was 4 (min = 0, max = 4) for reasonable explanations and 2 (min = 0, max = 2) for correct use. The highest possible score for the CR item was 7. Two research assistants independently coded the CR responses for all observations. The interrater reliability of scorings was 0.93 using intraclass correlation with absolute agreement (Shrout & Fleiss, 1979).

3.3.5. Screen recorder

To observe the participants' process of online searching and learning, we used “Screen Recorder Master” to record participants' screen during the entire task and to analyze their distraction behavior.

3.3.6. Distraction and irrelevant browsing behavior

Irrelevant browsing behaviors are defined as students' onscreen movement irrelevant with the task. Although the task duration was either 15 or 30 min, we asked students to flag the specific time when they thought they had completed the online searching task. Therefore, their behaviors were categorized as on-task and off-task. On-task behaviors were defined as students' search and reading behaviors before the time flag. Off-task behaviors were defined as students' onscreen movement after the time flag. The irrelevant browsing behaviors were coded and calculated in terms of frequency of irrelevant browsing, number of participants who engaged in irrelevant browsing, duration of irrelevant browsing, and percent of irrelevant browsing over the entire task duration. Two research assistants coded students' onscreen movement independently. The interrater reliability of coded browsing behaviors was 0.92 for the selected complete recordings from 8 out of 60 participants.

Specifically, students' browsing behaviors were categorized into on-task irrelevant browsing (On_IB), off-task irrelevant browsing (Off_IB), and total-task irrelevant browsing (Total_IB). The on-task irrelevant browsing rate was calculated as the duration of irrelevant browsing behavior before the time flag divided by the entire task duration. Off-task irrelevant-browsing rate, in turn, was calculated as the duration of irrelevant browsing behavior after the time flag divided by the entire task duration. Total irrelevant browsing rate was calculated as the duration of all irrelevant browsing divided by the entire task duration.

3.4. Statistical analysis

Two-way ANOVA and ANCOVA were used to examine the association between note-taking, time pressures, irrelevant browsing behavior (IB) rate, and online search performance. To further determine the causal effect of students' IB rates on their online search performance, multiple-regression analysis was used to establish how the on-task and off-task IB rates influenced online search performance, controlling for prior knowledge scores and gender.

R v3.4.1 (The R Core Team, 2017) and RStudio v1.0.143 (RStudio Team, 2017) were utilized to perform the analyses. The assumption of equal variances for ANOVA was examined with Bartlett's K-squared test (Snedecor & Cochran, 1980). Upon obtaining statistically significant ANOVA results, we conducted Tukey HSD tests as post-hoc tests if the equal variance assumption was met; otherwise, the Games-Howell test was used. The assumption of regression coefficient homogeneity was also checked before the ANCOVA was conducted. Chi-square test statistics (Altman, Machin, Bryant, & Gardner, 2000) were used to compare group percentage differences in irrelevant browsing behavior under high or low time pressure.

4. Result

4.1. Manipulation check of time stress

The validity of manipulating time pressure conditions was checked in terms of participants' perceived temporal demand and frustration level using NASA-TLX. The manipulation was intended to create a state of urgency for students to complete the task. That is, they were supposed to feel rushed under high time pressure but not frustrated.

The results of ANOVA tests in Table 1 show that students in the high time pressure (HTP) condition felt more rushed than those in the low time pressure (LTP) condition ($M_{\text{LTP-HTP}} = -0.983$, $F_{(1,\ 118)} = 4.85$, $p = .030$); however, their frustration scores did not differ significantly ($M_{\text{LTP-HTP}} = -0.100$, $F_{(1,\ 118)} = 0.22$, $p = .642$).

4.2. Descriptive statistics of irrelevant browsing behavior during tasks

Analysis of the on-screen movement records across high and low time pressure showed that 44 out of 60 participants (73.33%) conducted at least one of the following 11 kinds of task-irrelevant distraction behaviors during the online search task: visiting Facebook, doing online auction/shopping, watching nontask-related videos, visiting other social networking sites (such as Twitter, Instagram or Qzone, etc.), browsing news, visiting bulletin board system (BBS), playing online games, browsing official university websites, searching travel-related online information, engaging in other academic activities, or performing other online activities (such as reading comics or browsing online magazines). Due to the counterbalanced design, all participants experienced both the high and low pressure conditions. Among the 60 participants, 42 (70.00%) used the Internet for task-irrelevant behavior under low time pressure whereas 27 (45.00%) used the Internet for task-irrelevant behavior under high time pressure, $\Delta_{\%} = 25\%$ with $\chi^2(1) = 7.61$, $p < .01$ & 95% CI [6.19%, 42.03%].

Types and the durations of irrelevant browsing behaviors under high/low time pressure conditions were tabulated in Table 2. As illustrated, frequencies and durations of total task-irrelevant browsing behaviors were higher under low time pressure than under high time pressure across all categories of activities (e.g., $\#^{LTP}_{Total\_IB} = 257 > \#^{HTP}_{Total\_IB} = 105$; $duration^{LTP}_{Total\_IB} = 12{:}\ 13{:}\ 43 > duration^{HTP}_{T\_IB} = 02{:}\ 44{:}\ 04$).

Specifically, under low time pressure, visiting Facebook took up 39.21% of the total irrelevant browsing duration, followed by online auction/shopping (12.37%), watching Youtube videos (10.14%), browsing travel information (10.06%), and others, such as reading online comics and magazine (8.68%). Under high time pressure, online auction/shopping took up 19.94% of the total irrelevant browsing duration, followed by watching Youtube videos (19.15%), visiting Facebook (18.65%), others (16.39%), and browsing travel information (12.07%).

We further broke down irrelevant browsing behavior into on-task, off-task, and total-task irrelevant browsing, to examine students' distraction patterns. Table 3 exhibits the three periods of irrelevant browsing in terms of frequency, duration, and average percent of distraction over the designated task time. As above, the frequency and duration of distraction were higher under low time pressure than under high time pressure. Due to different durations of low/high time pressure conditions, we took the ratio of the distraction duration by total task duration as the index of the distraction ratio for the following analyses. As shown in Table 3, participants under low time pressure engaged, on average, in 39.31% of total irrelevant browsing compared to 22.96% for participants under high time pressure. Students under high time pressure exhibited only 8.41% of on-task irrelevant browsing compared to 15.05% for those under low time pressure. Off-task irrelevant browsing was also higher for participants in the low-pressure (24.26%) than those in the high-pressure condition (14.55%).

4.3. Analysis of variance (ANOVA) on irrelevant browsing rates

We performed a two-way factorial ANOVA of time pressure and note-taking strategy on On_IB, Off_IB, and Total_IB rate using R programming. Except for the effect of note-taking on On_IB, the assumption of equal variances across different time pressure and note-taking conditions was met (e.g., for Total_IB, Bartlett's K-squared = 0.135, $df = 1$, $p = .713$ for time pressure; Bartlett's K-squared = 2.89, $df = 2$, $p = .235$ for note-taking strategy).

As shown in Table 4 (a), both time pressure and note-taking strategy had differential effects on Total_IB rate ($F = 5.03$, $p = .027$, $\eta^2_{\text{partial}} = 4.20\,\%$ for time pressure, and $F = 3.39$, $p = .037$, $\eta^2_{\text{partial}} = 5.60\,\%$ for note-taking). Students in the high time pressure condition had a lower irrelevant browsing rate than those in the low

Table 1
Manipulation Checks of the Effects of Time Pressure Conditions on NASA-TLX Temporal Demand Scores and Frustration Level Scores.

Source	*Sum of Square*	*df*	*Mean Square*	*F*	*p*	η^2	*Post-hoc*
(a) NASA-TLX Temporal Demand by Time Pressure							
Time Pressure	29.01	1	29.01	4.85	.030	.04	HTP > LTP
Residuals	705.58	118	5.98				
Total	734.59	119					
Note. DV: NASA-TLX Temporal demand item score. Bartlett's K-squared = 2.844, *df* = 1 *p* = .092.							
(b) NASA-TLX Frustration by Time Pressure							
Time Pressure	0.30	1	0.30	0.22	.642	< .01	N.A.
Residuals	162.90	118	1.381				
Total	734.59	119					
Note. DV: NASA-TLX Frustration level item score. Bartlett's K-squared = 0.029, *df* = 1 *p* = .866.							

Table 2
Irrelevant Browsing Behaviors and Their Duration in Low and High Time Pressure Conditions.

Irrelevant browsing Behaviors	Low Time Pressure (30 min)				High Time Pressure (15 min)			
	# of IB.	# of ppl.	Duration	Avg. %	# of IB.	# of ppl.	Duration	Avg. %
Facebook	99	42	04:51:58	39.21%	37	24	00:30:39	18.68%
Auction/Shopping	23	10	01:32:09	12.37%	10	7	00:32:43	19.94%
Youtube	49	16	01:15:29	10.14%	19	11	00:31:25	19.15%
BBS	11	8	00:45:07	6.06%	4	3	00:06:00	3.66%
News	12	10	00:39:01	5.23%	2	2	00:07:55	4.83%
Other SNS	5	3	00:20:41	2.77%	2	1	00:06:33	3.99%
Online Game	3	1	00:05:31	0.74%				
Academics	9	3	00:11:04	1.48%				
Travel	16	11	01:14:55	10.06%	8	5	00:19:48	12.07%
Others	28	17	01:04:41	8.68%	21	13	00:26:53	16.39%
University Websites	2	1	00:13:07	1.76%	2	2	00:02:08	1.30%
Total	257	122	12:13:43	100.00%	105	68	02:44:04	100.00%

Note. # of IB.: frequency of certain irrelevant browsing behavior; # of ppl.: number of participants with certain IB; Duration: length of the IB duration with the value format of hh:mm:ss; Avg. %: rate of the duration of certain IB divided by the total duration of IB activities. Irrelevant browsing behaviors include (a) visiting Facebook, (b) doing online auction or shopping, (c) watching nontask-related videos, (d) visiting bulletin board system (BBS), (e) browsing the news, (f) visiting other social networking sites, (g) playing online games, (h) doing other academic activities, (i) searching traveling-related online information, (j) engaging in other online activities (such as reading comics or browsing online magazines), and (k) browsing official university websites.

time pressure condition ($M_{\text{LTP-HTP}} = 0.154$, $p = .001$, *Cohen's* $d = 0.578$). Moreover, students taking matrix notes had a lower irrelevant browsing rate than those in the conventional note or note-free conditions ($M_{\text{conventional-matrix}} = 0.192$, $p = .003$, $d = 0.785$; $M_{\text{free-matrix}} = 0.190$, $p = .003$, $d = 0.715$). The Cohen's d effect sizes were medium to large, ranging from 0.578 to 0.785.

As shown in Table 4(b), both time pressure and note-taking strategy had differential effects on On_IB rate ($F = 5.28$, $p = .023$, $\eta^2_{\text{partial}} = 4.40\,\%$ for time pressure and $F = 9.32$, $p < .001$, $\eta^2_{\text{partial}} = 14.10\,\%$ for note-taking). The variance-explained measure (i.e. $\eta^2_{\text{partial},note\rightarrow on\_IB} = 14.10\,\%$ v.s. $\eta^2_{\text{partial},note\rightarrow Total\_IB} = 5.60\,\%$) of the note-taking condition was more than doubled the previous analysis with Total_IB. Students taking matrix notes had a lower irrelevant browsing rate than those in the conventional note or note-free conditions (the Game-Howell test, $M_{\text{conventional-matrix}} = 0.085$, $p = .018$, $d = 0.690$; $M_{\text{free-matrix}} = 0.154$, $p < .001$, $d = 0.944$). Students in the high time pressure condition had a lower irrelevant browsing rate than those in the low time pressure condition ($M_{\text{LTP-HTP}} = 0.066$, $p = .023$, $d = 0.396$). The Cohen's d effect sizes were medium to large, ranging from 0.396 to 0.944. As for the Off_IB shown in Table 4(c), neither time pressure nor note-taking strategy had a significant effect on Off_IB rate, meaning students in each condition had a similar irrelevant browsing rate after they finished the online search tasks.

4.4. Analysis of covariance (ANCOVA) on online search performance

We performed a two-way factorial ANCOVA with time pressure and note-taking strategy as the independent factors and prior knowledge as a covariate on the T/F items in online search performance. The assumption of equal variances across different time pressure and note-taking conditions was met (Bartlett's K-squared = 0.482, $df = 1$, $p = .487$ for time pressure; Bartlett's K-squared = 0.860, $df = 2$, $p = .650$ for note-taking strategy). Likewise, the assumption of homogeneous regression coefficients also held ($F = 1.586$, $p = .209$ for prior knowledge×note-taking; $F = 0.004$, $p = .209$ for prior knowledge×time pressure; $F = 0.399$, $p = .672$ for prior knowledge×note-taking×time pressure). As shown in Table 5, the covariate of prior knowledge ($F = 12.75$, $p < .001$, $\eta^2_{\text{partial}} = 10.1\,\%$) and the factor of note-taking strategy ($F = 7.00$, $p = .001$, $\eta^2_{\text{partial}} = 11.02\,\%$) were statistically significant on T/F items. That is, after controlling for prior knowledge, students taking matrix notes still performed better in the T/F items than those in the conventional note or note-free conditions ($M_{\text{conventional-matrix}} = -1.30$, $p = .002$; $M_{\text{free-matrix}} = -1.73$, $p < .001$).[1]

The CR test was administered at the end of each experimental block for 10 min. Each student experienced both the high and the low time pressure condition. Therefore, we performed the one-way ANCOVA with note-taking strategy as the independent factor and prior knowledge as the covariate on the CR test. Likewise, the assumption of

[1] Cohen's d doesn't apply in the ANCOVA-like analysis.

Table 3
Frequency, Duration, and Average Rate of On-Task, Off-Task, and Total-Task Irrelevant Browsing Behaviors.

Time Pressure Condition (Task Duration)	On-Task Irrelevant Browsing Behaviors				Off-Task Irrelevant Browsing Behaviors				Total-Task Irrelevant Browsing Behaviors			
	# of IB.	Duration		% of IB	# of IB.	Duration		% of IB	# of IB.	Duration		% of IB
		M	*SD*			*M*	*SD*			*M*	*SD*	
Low (30 min)	168	04:31	05:35	15.05%	89	7:17	07:12	24.26%	257	11:48	08:04	39.31%
High (15 min)	60	01:16	02:12	8.41%	45	2:11	03:23	14.55%	105	03:27	04:00	22.96%

Note. # of IB.: Frequency of irrelevant browsing behaviors; Duration: duration of the irrelevant browsing behavior with the value format of mm:ss; % of IB: rate of the duration of certain irrelevant browsing behaviors divided by the total task duration under the time pressure condition.

homogeneous regression coefficients also held ($F = 0.318$, $p = .729$ for prior knowledge×note-taking). As shown in Table 6, only note-taking strategy had a differential effect on the CR test ($F = 3.64$, $p = .033$, $\eta^2 = 11.88\ \%$). That is, after controlling for prior knowledge, students taking matrix notes performed better than those in the note-free condition ($M_{\text{free-matrix}} = -1.83$, $p = .025$); however, the scores were not statistically different for those in the matrix note and conventional note conditions ($M_{\text{conventional-matrix}} = -0.55$, $p = .407$).

4.5. Results of multiple regression on online search performance

To investigate the effect of factors and variables that were predictive of university students' online search performance, we performed a multiple-regression analysis on T/F items with On_IB rate, Off_IB rate, time pressure, and note-taking strategy as the independent variables, controlling for prior knowled-ge and gender. As shown in Table 7, this regression model explained 23.93% ($F_{(7,\ 112)} = 5.033$, $p < .001$) of the variance for students' online-search performance on T/F items. All the variance inflation factor (VIF) values for the independent variables were within the cutoff point of 10, indicating no multicollinearity problem (Hair, Black, Babin, & Anderson, 2010). Thus, prior knowledge, On_IB, and note-taking strategy predicted online-search performance on T/F items. For every one-point increase in prior knowledge, students' T/F scores increased by 0.49 points. For every one-percent increase in on-task irrelevant browsing, T/F scores decreased by 2.14 points out of total 15 points, holding all other predictors constant. Moreover, on average, students in the matrix note condition scored higher on T/F items than those in the conventional note condition by 1.08 points, and they also scored higher than those in the note-free condition by 1.12 points. Male and female students do not significantly differ on their online-search performance with the intervention of note-taking and time pressure conditions.

5. Discussion

Digital distraction has grown into a major concern with regard to its potential for impairing students' learning and performance (Calderwood, Ackerman, & Conklin, 2014; Carrier et al., 2015; Wu, 2017). Based on the load theory of attention and cognitive control, the current study applied a randomized control block with a counter-balanced research design to test the effect of note-taking strategies and time pressure on university students' task-irrelevant browsing behavior

Table 4
Two-way ANOVA results of note-taking and time pressure on total task irrelevant browsing rate, on-task irrelevant browsing rate, and off-task irrelevant browsing rate.

Source	*Sum of Square*	*df*	*Mean Square*	*F*	*p*	$\eta^2_{partial}$	*Post-Hoc*
(a) Total Irrelevant Browsing by Note-Taking and Time Pressure							
Note-Taking	0.44	2	0.22	3.39	.037	.056	Convention > Matrix Note free > Matrix
Time Pressure	0.33	1	0.33	5.03	.027	.042	LTP > HTP
NT×TP	0.10	2	0.05	0.74	.479	.013	N.A.
Residuals	7.37	114	0.06				
Total	8.24	119					
Note. DV: Total Irrelevant Browsing Rate. For Note-Taking: Bartlett's K-squared = 2.893, *df* = 2 *p* = .235. For Time Pressure: Bartlett's K-squared = 0.134, *df* = 1 *p* = .713.							
(b) On-task irrelevant browsing by note-taking and time pressure							
Note-Taking	0.47	2	0.24	9.32	< .001	.141	Convention > Matrix Note free > Matrix
Time Pressure	0.13	1	0.13	5.28	.023	.044	LTP > HTP
NT×TP	0.003	2	0.001	0.05	.951	< .001	N.A.
Residuals	2.90	114	0.03				
Total	3.50	119					
Note. DV: On-Task Irrelevant Browsing Rate. For Note-Taking: Bartlett's K-squared = 35.282, *df* = 2, *p* < .01. For Time Pressure: Bartlett's K-squared = 3.484, *df* = 1, *p* = .062.							
(c) Off-task irrelevant browsing by note-taking and time pressure							
Note-Taking	0.20	2	0.10	2.04	.135	.034	N.A.
Time Pressure	0.16	1	0.16	3.26	.073	.028	N.A.
NT×TP	0.11	2	0.06	1.18	.312	.020	N.A.
Residuals	5.56	114	0.05				
Total	6.03	119					
Note. DV: Off-Task Irrelevant Browsing Rate. For Note-Taking: Bartlett's K-squared = 1.098, *df* = 2 *p* = .577. For Time Pressure: Bartlett's K-squared = 0.036, *df* = 1 *p* = .849.							

Table 5
ANCOVA results of note-taking and time pressure on online search performance controlling for prior knowledge.

Source	*Sum of Square*	*df*	*Mean Square*	*F*	*p*	$\eta^2_{partial}$	*Post-Hoc*
Cov: Prior Knowledge	34.85	1	34.85	12.75	< .001	.101	
Note-Taking	38.26	2	19.13	6.99	.001	.110	Matrix > Convention Matrix > Note free
Time Pressure	4.56	1	4.56	1.67	.199	.015	
NT×TP	0.65	2	0.33	0.12	.887	.002	
Residuals	308.95	113	2.73				
Total	387.27	119					

Note. DV: Posttest score. For Note-Taking: Bartlett's K-squared = 0.861, $df = 2$, $p = .650$. For Time Pressure: Bartlett's K-squared = 0.483, $df = 1$, $p = .487$. TYPE I sum of square was used, and prior knowledge was included as covariate.

Table 6
ANCOVA results of note-taking on constructed response score controlled by prior knowledge test score.

Source	*Sum of Square*	*df*	*Mean Square*	*F*	*p*	$\eta^2_{partial}$	*Post-Hoc*
Cov: Prior Knowledge	2.53	1	2.53	1.39	0.243	0.025	
Note-Taking	13.24	2	6.62	3.64	0.033	0.118	Matrix > Note free
Residuals	98.22	54	1.82				
Total	113.99	57					

Note. DV: Constructed Response score. For Note-Taking: Bartlett's K-squared = 3.058, $df = 2$, $p = .217$. TYPE I sum of square was used, and prior knowledge was included as covariate (Cov.).

Table 7
Results of the multiple-regression analysis of online search performance regressed on on- and off-task irrelevant browsing rates, time pressure, and note-taking strategy, controlled by prior knowledge and gender.

Predictors	*B*	*β*	*SE*	*t*	*p*		*VIF*
Prior knowledge	0.49	.27	.15	3.33	< .001	**	1.00
On-task Irrelevant Browsing rate	−2.14	-.19	1.02	−2.10	.038	*	1.23
Off-task Irrelevant Browsing rate	−0.25	-.03	.74	−0.34	.733		1.12
High time pressure	−0.55	-.14	.33	−1.68	.095		1.10
D1: Conventional vs. Matrix Note	−1.08	-.27	.40	−2.68	.009	**	1.23
D2: Note free vs. Matrix Note	−1.12	-.28	.41	−2.67	.009	**	1.23
Male	−0.40	-.10	.33	−1.18	.240		1.04

Note. DV: Posttest score. $R^2 = 23.93\%$, with $F(7, 112) = 5.033$, $p < .001$.
$^*p < .05$; $^{**}p < .01$.
D1: Conventional note vs. matrix note; D2: Note free vs. matrix note; the matrix note group was set as the reference group for these two dummy-coded variables.
VIF: Variance inflation factor, *VIF* < 10 indicates no severe multicollinearity issue for the predictor.

and online search performance. The findings of this research have both theoretical and practical significance. From a theoretical perspective, we applied the cognitive control mechanisms of attention to demonstrate the effect of note-taking and time pressure in reducing irrelevant browsing and enhancing online search performance. From a practical perspective, the study results may inform prevention and intervention strategies to reduce distraction and improve learning effectiveness. Below we discuss the findings with suggestions for instructional practice.

5.1. Irrelevant browsing during online search and effect of note-taking strategy and time pressure on distraction

In response to the first research question, across all participants we discovered that Facebook was the most prominent distraction source. Forty-two participants (70%) visited Facebook, and this took up the largest proportion of distraction duration (39.21%) during online search under low time pressure. Aagaard (2015) claimed that students are attracted to Facebook mainly through habitual distraction. Flanigan and Babchuk (2015) found that students use social media consciously or unconsciously, either as a reflex to check Facebook or as an intentional action to stop things at hand and turn their attention to Facebook.

The results of the current study coincided with arguments from the above studies. However, when time pressure was imposed on the search task, irrelevant browsing duration to Facebook dropped significantly (18.68%) under high time pressure for 24 participants (40%). Moreover, the number of participants who engaged in irrelevant browsing behavior, the number of irrelevant browsing behaviors across participants, and the duration of irrelevant browsing also dropped significantly under high time pressure compared with low time pressure. Therefore, time pressure may help participants inhibit task-irrelevant stimuli to avoid distraction. Alternatively, it is likely that time pressure creates specific time constraint that motivates participants in completing their task within the designated time so that they could have a "technology break" (Rosen, Carrier, & Cheever, 2013) to satisfy their urges to check messages or browse their desired content after finishing the task.

In response to the second research question, different note-taking strategies and time pressure settings led to different levels of irrelevant browsing during the search task. Specifically, students in the matrix note condition had a lower irrelevant browsing rate than those in the conventional note condition and in the note-free condition. Consistent with the load theory of attention and cognitive control (Lavie et al., 2004), note-taking may facilitate top-down selection process and reduce interferences from distractors. Compared with conventional notes, matrix notes allow information to be processed at a higher semantic level so that a judgement about relevance for the current topic and categories can guide attention during the online search. These exact dimensions for note-taking may maintain learners' attention to extract and select relevant information and inhibit task-irrelevant stimuli.

Moreover, students in the high time pressure condition had a lower irrelevant browsing rate than their counterparts during online search, which confirmed our conjecture that time pressure may make active cognitive control of attention more salient to sort out priority events and prevent interruption from distractors. These findings are in line with prior studies where participants initiated their active control under high time pressure to protect their goal in the probe task to indicate the direction of arrows (Qi et al., 2018) and in the selective attention task to reduce Stroop interference, where the name of a color is presented in a color not denoted by the name (Chajut & Algom, 2003).

Our results suggest that time pressure may help maintain task-processing priorities through the active cognitive control mechanism to guide behavior in line with major goals, so that students' attention can focus on the current search task for valid cues and avoid task-irrelevant responses (Broeker et al., 2018).

5.2. Effect of note-taking strategy and time pressure on online search performance

In response to the third research question, note-taking strategy had a differential effect on online-search performance, but time pressure did not. Consistent with the findings of previous research (Jairam & Kiewra, 2010; Kauffman, 2004; Kauffman, Zhao, & Yang, 2011), students in the matrix note condition performed better than those in the other conditions. Specifically, students taking matrix notes scored higher than those in the conventional note or note free conditions on the TF items; they also scored higher than those in the note-free condition on the CR items.

Kauffman and Kiewra (2010) noted that signaling, extraction, and localization are the reasons why matrix notes are effective. Signaling is the level of text that presents the cued information. Extraction is the process of sifting important content from extraneous information. Finally, localization is the physical proximity of related contents. In the current study, matrix notes signaled the major points using two-dimensional tables for topics and categories. Then participants followed the structure to extract relevant content from the intervening information. Finally, similar contents were placed close together for comparison and contrast using graphic organizers.

However, students taking matrix notes and those taking conventional notes did not differ on their mean CR scores. According to Jairam and Kiewra (2010), students taking conventional notes may create their notes in a linear format and produce piecemeal learning and redundant strategies. Nevertheless, note-taking still serves storage and encoding functions (Jansen, Lakens, & IJsselsteijn, 2017). Based on our findings with regard to the CR item, it seemed that the conventional notes could somehow maintain students' attention and help them store and encode their search result. In fact, note-taking bolstered connection of information in part due to the generation effect, which suggests that people retain information better when they generate material instead of studying what is given to them (Piolat, Olive, & Kellogg, 2005). Therefore, we suggest that effective note-taking strategies such as matrix notes be used by university students while studying online to facilitate extraction and organization of information. Though online searches are strongly goal-directed tasks, literature still documented a phenomenon of disorientation during online search characterized by a feeling of getting lost or not knowing what to do with their search (Hsieh & Tsai, 2014; Tsai, Hsu, & Tsai, 2012; Çoklar, Yaman, & Yurdakul, 2017). Though matrix notes seem to be applicable only to pre-structured materials, they may also serve as an organizer for learners to glean basic information about definitions, features, and examples of the topic. Thus, training students to plan on their online search and create matrix notes based on categories across subjects may be necessary. Moreover, if taking matrix notes is not possible, we suggest taking conventional free notes to maintain attention and foster retention and connection of information.

Although research showed that students' reading comprehension was enhanced under mild time pressure whereas they performed poorly under severe time pressure (Walczyk et al., 1999), time pressure did not affect students' online search performance in the current study. Time pressure may quicken the processing speed but at the cost of more textual ingredient information being skipped in brand selection (Pieters & Warlop, 1999) and more behavioral errors being committed in a maze task (Slobounov et al., 2000) or in an arithmetic task (Qi et al., 2018). Nevertheless, appropriate time pressure may activate higher level of arousal of motivation and efforts (Walczyk et al., 1999). It is likely that the effect of time pressure materializes through different (indirect) mechanisms. In the following section, we further investigate that possibility.

5.3. Factors that enhance online search performance

In response to the fourth research questions, we constructed an integrative model to evaluate the effect of different factors and variables on online search performance. We found that prior knowledge, on-task irrelevant browsing rate, and note-taking strategy predicted online search performance, whereas off-task irrelevant browsing rate, time pressure, and gender did not. Prior knowledge may create a hook for in-depth learning as evidenced in several studies (Ozuru, Dempsey, & McNamara, 2009; Rupley & Slough, 2010; Salmerón, Kintsch, & Caãs, 2006). After controlling for the effect of prior knowledge, we found that on-task irrelevant browsing rate and note-taking strategy still influenced online search performance. Although time pressure did not directly affect online search performance, as shown in the effect of time pressure on irrelevant browsing, participants in the high time pressure condition exhibited significantly lower irrelevant browsing rates than those in the low time pressure. Therefore, as we presumed that time pressure might impact online search performance through an indirect mechanism, results of the regression analysis revealed that on-task irrelevant browsing rate (a related construct of time pressure) was more predictive of online search performance. Based on findings of the integrative model, we found providing learning instructions such as time pressure and cognitive aids such as structured note-taking may enhance students' online search performance.

6. Conclusion and implication

This study applied the load theory of cognitive control of attention to suggest the use of note-taking and time pressure in reducing distraction and enhancing performance in an online search task among university students. Research showed that people have poor perception about time. They perceived that time passage and time duration was longer and slower for less entertaining tasks, while switching between more entertaining or less entertaining tasks were shorter and faster (Xu & David, 2018). Moreover, research showed that participants with better self-regulation ability had less switching between browser tabs; however, when instructions were imposed on participants to perform tasks in a sequential order, their task performance was better than those in the free switching condition (Szumowska, Popławska-Boruc, Kuś, Osowiecka, & Kramarczyk, 2018).

From the perspective of active cognitive control of attention (Lavie et al., 2004), time pressure can ensure that response is properly controlled by goal-relevant rather than goal-irrelevant stimuli. Therefore, providing learning instructions and cognitive aids may benefit students' learning performance within the open-ended internet environment. Instead of urging students to cut down on their distraction, we added to the literature that imposing time pressure on online search tasks for learning purposes that were commonly regarded as less entertaining may assist learners in active control of their time and in management of their tasks to avoid irrelevant browsing. We suggest that students create mild time pressure while studying online by setting time limits for a given task. For example, Do Not Disturb software as introduced in Biskjaer, Dalsgaard, and Halskov (2016) can also be used to set time pressure along with the functions to temporarily restrict Internet access and block irrelevant websites. Alternatively, artificial intelligence (e.g., Amazon Alexa) can be used to keep track of time during the task. Herein, students may guide their attention and learning through external sources (external regulation) to gradually establish their self-regulation (Vermunt & Donche, 2017). Compared with students in the matrix note condition, students in the conventional note or note-free conditions performed significantly poorer on online search tasks. Therefore, taking matrix notes may be helpful in enhancing online search performance and reducing irrelevant distraction due to its two-dimensional cross-tables that facilitate selecting, extracting, and comparing information across categories and subjects. We suggest that university students apply matrix notes while studying online to enhance their selection, organization, and association of information.

The study findings, however, should be interpreted in light of limitations. First, though sample size of the current study was relatively small (n = 60), we obtained significant results despite this constraint with the proposed experimental design. Future study can be conducted with a larger sample to test the robustness of the result. Second, time pressure did not cause frustration in the current sample but the generalizability of this result to other cultures may warrant future investigation. Finally, the structure of matrix notes was given to participants in this study. Future research can be conducted to examine how students' ability to create outlines for the matrix note affects their online search performance and distracted behavior.

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