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RESEARCH ARTICLE

Mental workload variations during different cognitive office tasks with social media interruptions

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ABSTRACT

Interruption at work by social media (SM) is a pervasive phenomenon. This study investigated the impact of SM interruptions and task cognitive levels on mental workload (MWL) and physiological indexes. Each subject performed six simulated computer tasks differentiated by two factors: task cognitive level and performing condition. MWL was reflected through three categories of data: perceived mental workload, physiological indexes, and primary task performance. The results revealed significant effects of SM interruptions on heart rate, low-frequency/high-frequency (LF/HF) ratio, and skin conductance. ANOVA results showed there were main effects of task cognitive level on LF/HF and skin conductance. These effects during interrupted tasks were more profound. In addition, participants experienced higher MWL and recorded lower primary task performance in the knowledge-based task than the rule- and skill-based tasks. Our findings can guide managers and employees regarding appropriate use of SM in the workplace and better managing interruption and workload.

Practitioner Summary: Office workers suffer from increased overall mental workload due to unpredictable interruptions while working. This study shows that participants' mental workload increased when receiving SM interruptions, which was more profound during complex tasks. This highlights the importance of SM interruptions management for employees' health, performance, and mobile application developers.

Abbreviations: ANOVA: analysis of variance; DSSQ: dundee stress state questionnaire; ECG: electrocardiographic; EDA: electrodermal activity; EEG: electroencephalographic; HPA: hypothalamus-pituitaryadrenocortical; HR: heart rate; HRV: heart rate variability; LF/HF: low frequency/high frequency; MSDs: musculoskeletal disorders; MWL: mental workload; NN: normal to normal; RMS: root means square; RR: time duration between two successive R peaks; RT: response time; SC: skin conductance; SDNN: standard deviation of normal to normal; SM: social media; TCL: task cognitive level; TPC: task performing condition; WMC: working memory capacity

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Mental workload; social media; interruption; office work; psychophysiology

1. Introduction

Social media (SM) has become an inevitable part of people's personal and professional lives, profoundly changing how they interact with others and the content (Chen et al. 2021). Today, many people use SM worldwide (Hu et al. 2017; Kim, Sohn, and Choi 2011), and it is growing quickly (Leftheriotis and Giannakos 2014). By 2023, it is expected that around half of Earth's entire population (3.43 billion monthly) will be active SM users, spending on average 144 minutes per day using internet-enabled platforms (Statista 2021). Moreover, the number of office employees who use SM in the workplace increases along with increasing SM users (Cao et al. 2012; Nucleus Research 2009). Individuals use SM at work in three dimensions to fulfil their needs: social use, hedonic use, and cognitive use (Ali-Hassan, Nevo, and Wade 2015). The widespread use of online applications, whether at work or home, provides convenience to people, but it also has some "dark side" and negative outcomes such as frequent interruptions, particularly at work (Gupta, Li, and Sharda 2013; Addas and Pinsonneault 2018).

In practice, interruptions while working are a necessary part of most work environments. Employees facing frequent interruptions perceive their work as less predictable and controllable (Zijlstra et al. 1999), which are associated with increased workload, stress, fatigue, and

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frustration (Tucker and Spear 2006). Research has found that individuals at work are disrupted four times per hour on average, and online interruptions are the most common (Brumby, Janssen, and Mark 2019). For instance, frequent workflow interruptions in healthcare professionals (e.g. responding to colleague's question) often lead to suspension of the focal task (e.g. to prescribe medication), and Weigl et al. (2012) found that overall workflow interruptions were significantly related to doctors' workload. Healthcare specialists often need to carry out complex tasks demanding contiguous attention, but an interruption is an obstacle to effective completion and diminishes work performance (Zijlstra et al. 1999; Greiner et al. 1997). A field study of interruption management practices in everyday cell phone users reported that the caller influenced subjects' decisions (87.4%), mental state of mind (34.9%), and the place/activity/people around (43%) (Grandhi and Jones 2010). Therefore, it is crucial for management to understand how these transitions affect the mental workload (MWL), performance, and well-being.

Concerns about multi-tasking and interruptions while working have been growing due to the increasing proliferation of mobile technology (Mark, Iqbal, and Czerwinski 2017). In one study (Pielot, Church, and De Oliveira 2014), participants received an average of about 65 mobile notifications per day, and Kessler (2007) found that approximately 4 min are necessary for workers to re-engage to their original tasks after an interruption. Even worse, other studies estimate that 40% of employees fail to reorient to main tasks (Thompson 2005). Despite the existing research evidence, the effect of SM interruptions on office workers' MWL has not yet been sufficiently investigated. From a review paper that summarised the employee use of the public SM (Chen et al. 2021), the existing literature is most concerned with the impact of employees' use of SM on the overall work performance (Moqbel, Nevo, and Kock 2013; Charoensukmongkol 2014; Leftheriotis and Giannakos 2014; Cao et al. 2016; Huang and Liu 2017; Tulu 2017; Lee and Lee 2018; Yu et al. 2018; Cao and Yu 2019).

1.1. Interruption

Building on Jett and George's (2003) typology and Leroy, Schmidt, and Madjar (2021), there are five interruption types: intrusions, distractions, multitasking, breaks, and surprises. Switching attention is at the core of the interruption phenomenon; some cognitive and behavioural consequences of all interruptions types are common, while others are unique (Leroy, Schmidt, and Madjar 2021). It should be notable that because some interruptions (i.e. intrusions, distractions, and multitasking) are more cognitively demanding, their corresponding performance is marked by higher costs. For example, some unexpected emails require immediate responses that were not planned for and cause intrusions (Dabbish et al. 2005; Barley, Meyerson, and Grodal 2011). Distractions, such as mail alerts, loud voices, electronic distractions (e.g. phone alerts), often coming across in open offices, have been related to stress, lower job satisfaction, lower psychological well-being, and putting employees at higher physical injuries risks (Evans and Johnson 2000). Multitasking has been associated with greater stress levels, such as writing an email and listening to a podcast.

SM interruption greatly differs from other kind of interruptions at work (e.g. phone calls or emails) in that it is more frequent (easily over 100 per day), more complex (3 dimensions as mentioned above), and less predictable (may be from any 'friends' in one's social network, and may also be pushed notifications). In addition, SM interruptions may come from not only external cues (e.g. receiving a message), but also internal cues (Wilmer, Sherman, and Chein 2017). For example, when a user starts thinking about unanswered messages, he/she is already interrupted internally. When users are engaged in a task, mind wandering may result in internal distraction and lead to failure of attentional control (McVay and Kane 2010). For instance, Hollis and Was (2016) showed that students' minds frequently wandered to SM while learning online. So understanding how SM interruptions impact one's office task performance as well as mental workload has become an emerging interested topic.

SM interruptions may appear as intrusions, distractions, multitasking, breaks, or surprises in reality. However, in this study, we only focus on SM intrusions because intrusion is considered to be the most serious interruption type. Intrusions are characterised by switching one's attention from the current task to the interrupted task despite one would rather like to continue the current task (Leroy, Schmidt, and Madjar 2021). The unpredictable SM-resulted interruptions at work impair the continuity of cognitive processes and cause an attention switch, in case it is an intrusion-type event that requires an immediate response (Jett and George 2003; Monk, Trafton, and Boehm-Davis 2008).

1.2. Mental workload

MWL is the required subjective mental effort to respond to a task load (Gao et al. 2013). Former studies used task performance, subjective ratings (e.g. NASA-TLX), secondary task performance monitoring to evaluate MWL (Young et al. 2015).

Nowadays, the availability of wearable sensor technologies has suggested that it can be inferred from the measurement of physiological processes (Charles and Nixon 2019; Matthews et al. 2015). In comparison with performance and subjective measures, physiological signals possess better performance in terms of diagnostic ability, sensitivity, and non-intrusiveness (Parasuraman and Rizzo 2007; Zhao, Liu, and Shi 2018). There are a variety of physiological indicators that are used to measure MWL. These indicators include the way that the brain and body react to cognitive tasks, such as recording electrocardiographic (ECG) activity, electroencephalographic activity (EEG), electrodermal activity (EDA), eye movement, and blood pressure (Charles and Nixon 2019; Kramer 2020; Matthews et al. 2015; Young et al. 2015). Although MWL is multidimensional and difficult to observe directly (Hancock and Matthews 2019), previous studies have suggested that using combined indexes (subjective rating, task performance, and physiological signals) can reach satisfying accuracy (Ding et al. 2020). In this study, we also used a combination of subjective rating, primary task performance, and physiological signals to measure MWL.

1.3. Human cognitive behaviors taxonomy

While people in an office environment often have to deal with the coordination of multiple and simultaneous tasks, different complexity of tasks usually would require different levels of information processing resources, accordingly leading to different levels of MWL. Rasmussen (1983) developed an influential classification of the different kinds of information processing tasks to make a distinction between various levels of human cognitive behaviour, consisting of skill-, rule-, and knowledge-based behaviour. Skill-based behaviour is specified by using rote knowledge and usually controls performance by patterns of behaviour stored in long-term memory. Skill-based task performance typically involves strong signal-response activities that are smooth and relatively automatic (Swezey and Llaneras 1997). Typical examples are experimental tracking tasks. Rule-based behaviour is determined by using propositions in long-term memory (Rasmussen 1983). Usually, it occurs in familiar settings, which are controlled by a stored rule (Swezey and Llaneras 1997). The point here is that performance is goal-oriented but structured by feedforward control through a stored rule—'if the X conditions exist, then do Y.' Cognitive function for this type of behaviour is considerably more time-consuming and less automatic than for skill-based behaviour. Knowledge-based behaviour involves unfamiliar situations where no solutions are already available. In such cases, the user would have to exert considerable mental effort to handle the situation, and responses would be slow. Knowledge tasks typically involve a higher level of cognition, including decision-making, problem-solving, and planning relying on situation awareness (Sheridan 1997).

When task demands surpass available cognitive resources, MWL becomes overloaded, and performance may drop rapidly (Sharples and Megaw 2015). Cognitive load may also vary by the demand of different types of behaviour, and different cognitive behaviours may be related to various physiological reactions. In a recent pilot study from our group, we designed an experiment to check the effects of SM interruptions on office employees' reading and writing task MWL, but we did not consider the impact of task cognitive levels (Zahmat Doost and Zhang 2022). Therefore, this study considered different levels of cognitive tasks in exploring MWL variation.

To sum up, we aim to explore some findings to the following four questions experimentally:

1. How SM interruptions at work lead to MWL variations compared to the continuous condition? (factor TPC—*Task Performing Condition*: performing tasks with/without SM interruptions).
2. How MWL measurements change between different task cognitive levels? (factor TCL—*Task Cognitive Level:* skill-, rule-, and knowledge-based levels of tasks).
3. Is there any interaction effect between factor TPC and factor TCL on MWL measurements?
4. Can physiological signals (EDA and ECG), subjective rating (NASA-TLX), and behavioural measurements (primary task performance) detect MWL variations for different TPC and TCL settings?

2. Method

2.1. Study population

To calculate an appropriate sample size, an a-priori power analysis was applied using G*Power (version 3.1.9.6) (Faul et al. 2009) and the 'Cohen (1988)' effect size option. As for the factorial ANOVA, the sample size needs to be determined individually for each factor and each interaction. In this study, prior knowledge of the correlation among repeated measures (ρ), a non-sphericity correction (ε), and the effect size (based on $\eta^2 \approx 0.43$) were extracted from a pilot study with five subjects. The results at an alpha level of 0.05 and a power of 0.95 show that the sample size required to analyse the within-subjects factor TPC is 23, factor TCL is 20, and interaction between the two factors is 28. Therefore, we rounded the number of participants to 30.

Thirty office staff (sixteen females and fourteen males; age $= 44.8 \pm 14.8$ years) were recruited from two Chinese universities, sharing the same participants with our pilot study (another independent study) reported in Zahmat Doost and Zhang (2022). All selected participants were healthy with normal or corrected-to-normal vision and no mental or skin illness. Three items from the Dundee Stress State Questionnaire (DSSQ) (Matthews et al. 1999) scale were employed to gather participants' self-reported stress, anxiousness, and mood. Before the experiment, none of the participants reported that they had experienced stress, nervousness, or negative mood. Consent form was signed by participants after they were introduced to and agreed to the research protocol, which was approved by The Institutional Review Board of the Industral Engineering Department, Tsinghua University. An incentive of 150RMB ($\sim$23 US dollar) each was paid for their participation.

2.2. Apparatus

The different cognitive tasks were created using PsychoPy 3.0 and shown on a 13" Macbook screen with 1280 × 800 resolution; PsychoPy is a platform-independent experimental control system written in an interpreted Python language using completely free libraries. For the interrupted conditions, participant received incoming Wechat (A popular SM in China) messages and were notified to switch from the ongoing tasks to secondary tasks, which required them to fill out an online questionnaire on http://www.wjx.cn. The questionnaire included different types, e.g. watch a video and then answer a question, or read a text and answer a question, or ask them a key word searching question. The subjects sat about 60 cm away from the Laptop monitor in a quiet and normal lighting room. The physiological indexes, including non-invasive wearable electrocardiography (ECG) and electrodermal activity (EDA), were recorded through the ErgoLAB® cloud platform (Kingfar Technology Co., Ltd, Beijing, China). ErgoLAB® collects the physiological variation data of the participants in the actual mood without any limitations to do the

Figure 1. Experiment setup and placement of sensors.

tasks. Two electrode patches were attached to the left-hand middle and index fingers to collect the EDA raw data and an ear clip sensor was fastened to the left earlobe to measure ECG (Figure 1). Participants used scrubbing cream and a cotton swab to reduce the surface impedance of the skin. The root means square (RMS) of the signal was determined using a time constant of 128 ms. The sample rate of ECG was 1024 Hz and that of EDA was 64 Hz with a noise level of 1.6 μV. All of the electrodes were less than 5 kΩ during the experiment.

2.3. Procedure

This study tested the hypotheses in a repeated measures factorial design, with each participant receiving all conditions. Participants were advised to have a normal night sleep and avoid caffeinated drinking before the experiment. When participants arrived, the experimenter gave an overview of the experiment, and they practiced to be familiar with the rules and controls. Then, they were trained to use the computerised version of the NASA-Task Load Index (Hart and Staveland 1988) to report their perceived workload in the experiment.

The experiment used a mixed design that included 2 Task Performing Conditions (continuous vs. SM interrupted) × 3 Task Cognitive Levels (skill-, rule-, and knowledge-based primary tasks), and users completed a total of 6 tasks. Figure 2 presents a sequence comprising of primary tasks in continuous and interrupted conditions; (a) *continuous condition*: participants were instructed to complete three primary tasks eifficently and accurately to their best effort. After ending each primary task, the subject was required to immediately fill in the NASA-TLX questionnaire to report their perceived MWL during

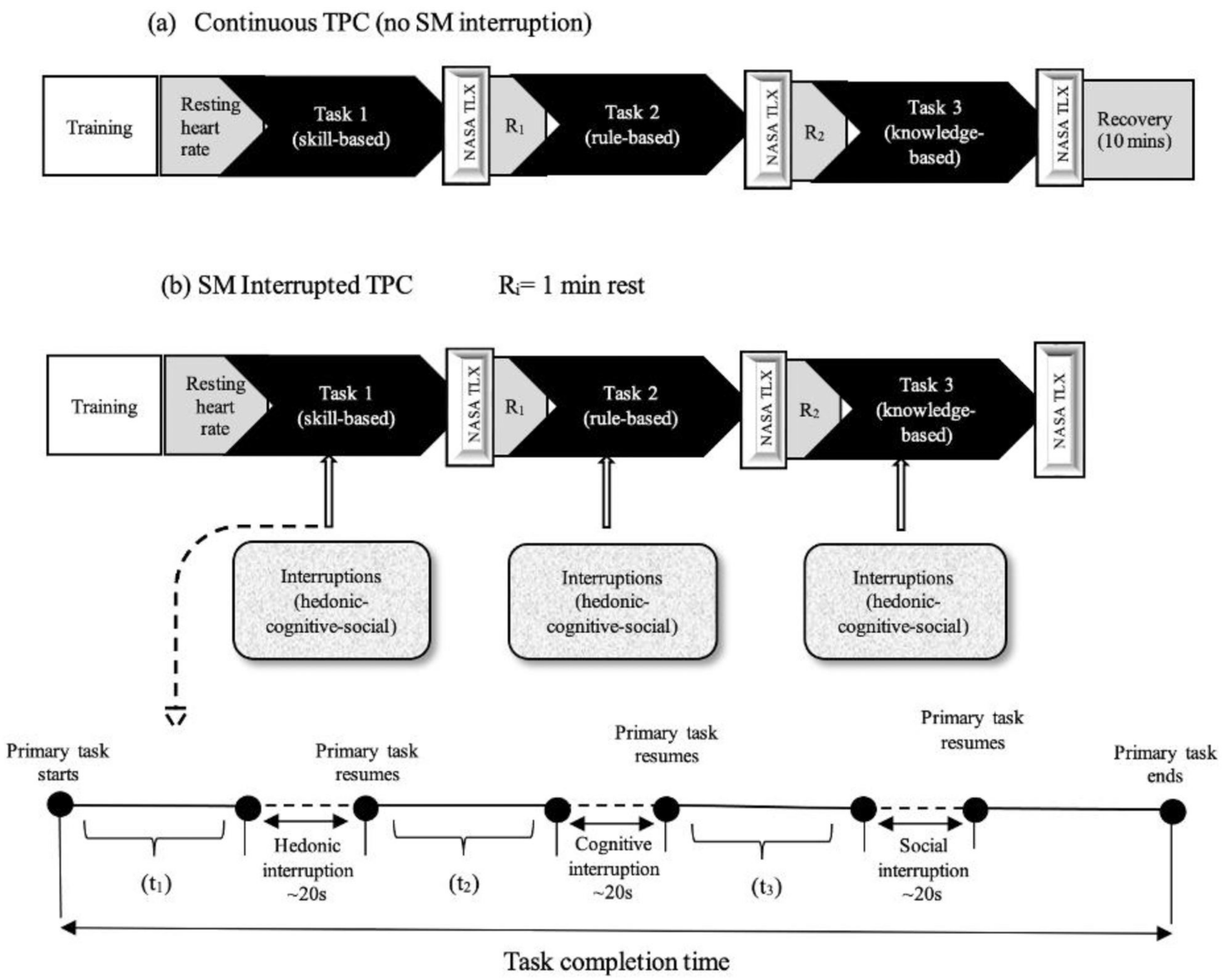

Figure 2. Overview of the experimental procedure (TPC: Task Performing Condition).

the just completed primary task. Participants took a rest for 10 min after completing the continuous tasks and then started the interrupted tasks; (b) *interrupted condition*: It was similar to the continuous condition. The only difference was that interruptions would occur when performing the primary tasks within uncertain time distance. Subjects experiencing the interrupted condition first also had 10 min rest before starting the continuous conditions. The sequence was counterbalanced. The presentation orders of the primary tasks (skill-, rule, and knowledge-based) and interruption tasks were randomised to minimise learning effects. The entire experimental session lasted about 60 min. Considering that some physiological parameters are sensitive, e.g. temperature, humidity, time of day, and season (Charles and Nixon 2019; Kramer 2020), all the participants were exposed to the same conditions of the laboratory environment in terms of temperature, light, and noise.

2.4. Task simulation

As shown in Figure 2, three categories of primary tasks were designed to elicit varying levels of human cognitive behaviour, including:

- *Skill*-based *task.* A visual tracking task was chosen to represent skill-based behaviour in this experiment. A red circle (the target) moved around the tracking area during the visual tracking task, and subjects were required to follow the target on the screen using their hands to control the mouse by clicking the right mouse button in the right place. The target appears 45 times on the screen in different positions; once participants click on the target, it will disappear and come up in the next point. Response time (s) (time needed to complete the task) and number of errors (number of clicking on the non-target place, which is tracked and saved through PsychoPy log) were recorded.

- *Rule-based task*. Participants were posed with a size classification task that required the use of a definite decision rule based on fundamental learning and extensive use of working memory for sequencing perceived information. Here, two objects of different sizes appeared on the screen, and the rule was choosing the bigger one by pressing the right or left key according to the place of the bigger object. This part also happened 45 times, and after pressing the key, the following two objects will appear. Response time and the number of errors (wrong responses tracked and saved through PsychoPy log) were recorded.
- *Knowledge-based task*. Participants were required to complete a problem-solving task. Subjects were asked to read a short story of the daily schedule of an administrative assistant and then modify the schedule to include additional activities (Leyman et al. 2004). Each scenario consisted of all critical information (e.g. activities, time needed for each activity, total available time). After analysing the scenario, the user filled the scheduled table. Response time and answers (to find the words wrongly filled in the schedule table) were recorded.

We designed the primary tasks with similar lengths, requiring about 2 min to complete. We refined the tasks from a pilot study with five users to improve clarity and roughly meet the target completion time. There was no time limit to complete all the tasks, and participants were asked to respond as accurately as possible. Two sets of similar tasks were designed, corresponding to the experiment condition of continuous and interrupted one each.

The interruption blocks were designed to distract an individual's attention and bring the primary task to a halt, interruption's handling and resumption. A survey (Ali-Hassan, Nevo, and Wade 2015) explored that individuals use SM at work for three purposes: social, hedonic, and cognitive; accordingly, so we made three different SM interruptions:

- *Hedonic interruption*. A short, fun video (20 s) was sent to the subjects through their cellphones. The subjects watched the video and then resumed the primary task.
- *Social interruption*. It had a received message from a friend about personal life (e.g. an invitation for a party at the weekend), and the participant should reply by selecting one of four suggested answers.
- *Cognitive interruption*. Included a short passage (∼3–4 sentences), and participants were required to read, find any names (∼2–3 names), and type them in the answer box.

The interrupting tasks were designed to last approximately 20 s and were refined based on a pilot study with five users. Because a user would receive three tasks from each category (during each of the primary tasks), we designed several sets of similar tasks. These interrupted task categories were selected because they are representative of SM interruptions that individuals often receive at work. Participants scanned the prepared QR code with their cellphones at the beginning of the interrupted condition. They then received three interruption tasks with different time distances (t_1, t_2, and t_3) during the first 2 min of each primary task.

2.5. Measurement and data analysis

In this study, both objective and subjective dependent variables were measured. The objective variables include the participants' physiological indexes (EDA and ECG) and primary task performance indexes (response time (RT) and the error rate of the primary tasks). The subjective variable is the evaluation of perceived MWL. These variables are explained in detail below.

ECG technology uses multiple sensors to measure the electrical activity of the heart. Cardiac activity can be analysed in the time or frequency domain. This work selected two metrics from the time domain (HR and SDNN) and one from the frequency domain (LF/HF). Heart rate (HR) is a time-domain measurement that is usually reported and is measured as the number of beats over a period of time, most often recorded per minute (Charles and Nixon 2019). SDNN is a standard deviation of RR interval (time duration between two successive R peaks) within the specified time. The ratio of LF (low frequency) and HF (high frequency) (LF/HF) is a frequency-domain method, and it is known as a measurement for Sympathovagal balance. LF was bandpass filtered within the range of 0.04–0.15 Hz and HF filtered within 0.15–0.4 Hz. Moreover, Electrodermal activity (EDA) measures the changes in electrical activity in the eccrine sweat glands controlled by the sympathetic nervous system (Charles and Nixon 2019). The EDA signals were bandpass filtered with the range of 0.05–500 Hz. The physiological indexes were selected based on the previous review (Charles and Nixon 2019; Ding et al. 2020). First, physiological signals were pre-processed through ErgoLAB®. Then, data was cleaned with

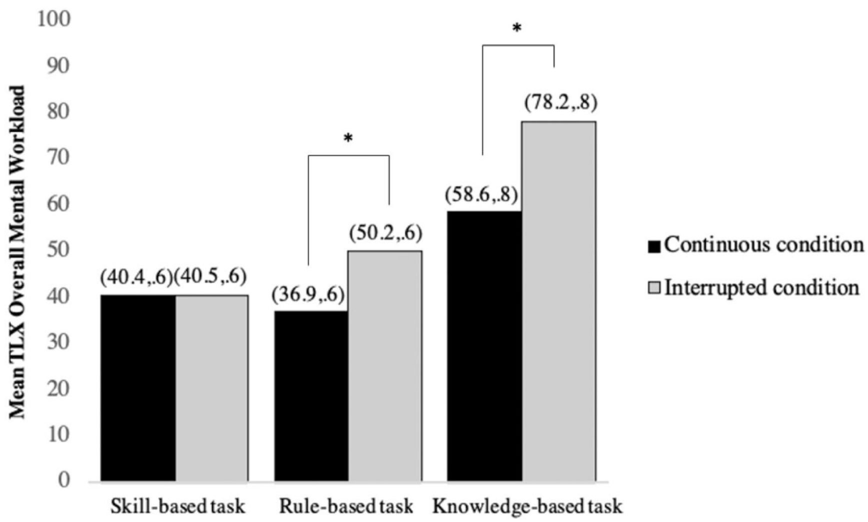

Figure 3. Comparisons of TLX overall for 3 cognitive level tasks under 2 performing conditions.
Note. The numbers above each bar represent the mean and standard deviation (mean, *SD*). * Shows the significant paired t-test.

wavelet denoising and root-mean-square (RMS) filtering. Baseline mean values were subtracted from each respective task data to perform baseline correction. The required recordings of physiological signals were the first 2-min segments for each task (six 2-min segments per participant). These were distinguished by screen recording made by ErgoLAB®.

Primary task performance was analysed using response time (RT) and the error rate of the main task at each level. RT includes the time spent completing each primary task from the time recording controlled by PsychoPy, and the error rate was the percentage of tasks that were not correctly solved.

From the subjective standpoint, this study used the NASA-TLX workload questionnaire (Hart 2006), which collected subjective MWL information. After completing a task, the participant fills out the NASA-TLX questionnaire to provide a self-reported MWL for each task. Only the overall workload score was of interest for this experiment (Hart and Staveland 1988).

To analyse the collected data, we used the two-way repeated-measures analysis of variance (ANOVA) to evaluate the impacts of factor TPC and TCL on dependent variables. The within-subject factors are TPC (continuous and interrupted) and TCL (the skill-, rule-, and knowledge-based). To fulfil the ANOVA assumptions, we conducted the residual normality and constant variance. The non-normal variables were transformed to the standard values using *Z*-score standardisation (Guyon and Elisseeff 2006). The Greenhouse-Geisser correction was applied to adjust degrees of freedom in case of significant Mauchy's test of sphericity ($p < 0.05$), and the effect size (η^2) is reported for all ANOVAs. Also, we analysed the pairwise differences with a paired *t*-test. The SPSS version 25.0 was used for analysis, and statistical significance was considered at $p < 0.05$.

3. Results

3.1. Self-reported mental workload levels

Figure 3 displays the overall workload (mean TLX) during different cognitive level tasks in continuous and interrupted conditions. The results indicated that the subjects perceived the continuous rule-based task as the lowest and interrupted knowledge-based the highest cognitive load. A two-way ANOVA with repeated measures showed that there was a main effect of TPC on overall MWL with $F(1, 29) = 268.72$, $p < 0.05$, $\eta^2 = 0.903$. It also showed a significant effect of TCL on overall MWL with $F(2, 58) = 874.12$, $p < 0.05$, $\eta^2 = 0.968$. There was a significant interaction between factor TPC and factor TCL on overall MWL with $F(2, 58) = 102.198$, $p < 0.05$, $\eta^2 = 0.779$.

Additionally, the paired t-tests showed the subjective rating of the knowledge- and rule-based tasks under the interrupted conditions are higher than those under the continuous conditions, but there was no significant difference for the skill-based task. Also, the paired *t*-tests showed that under the interrupted condition, the perceived MWL of the knowledge-based task was higher than that of the rule-based task and skill-based task ($t(29) = -20.99$; $t(29) = -19.26$, $p < 0.05$), and that of rule-based task was higher than that of skill-based task ($t(29) = -9.84$, $p < 0.05$). However, under the continuous condition, the perceived MWL of the rule-based task was lower than that of the skill-based task ($t(29) = 4.35$, $p < 0.05$).

Table 1. Summary of performance measures for each sub-task.

	Tasks under continuous condition						Tasks under interrupted condition					
	Skill-based		Rule-based		Knowledge-based		Skill-based		Rule-based		Knowledge-based	
Indexes	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*
Reaction time (s)	129.9	20.1	131.1	5.9	140.2	5.8	209.5	22.4	217.8	18.0	240.4	24.1
Error rate (%)	0	0	0	0	31.4	7.1	0	0	2.2	1.6	44.6	8.7

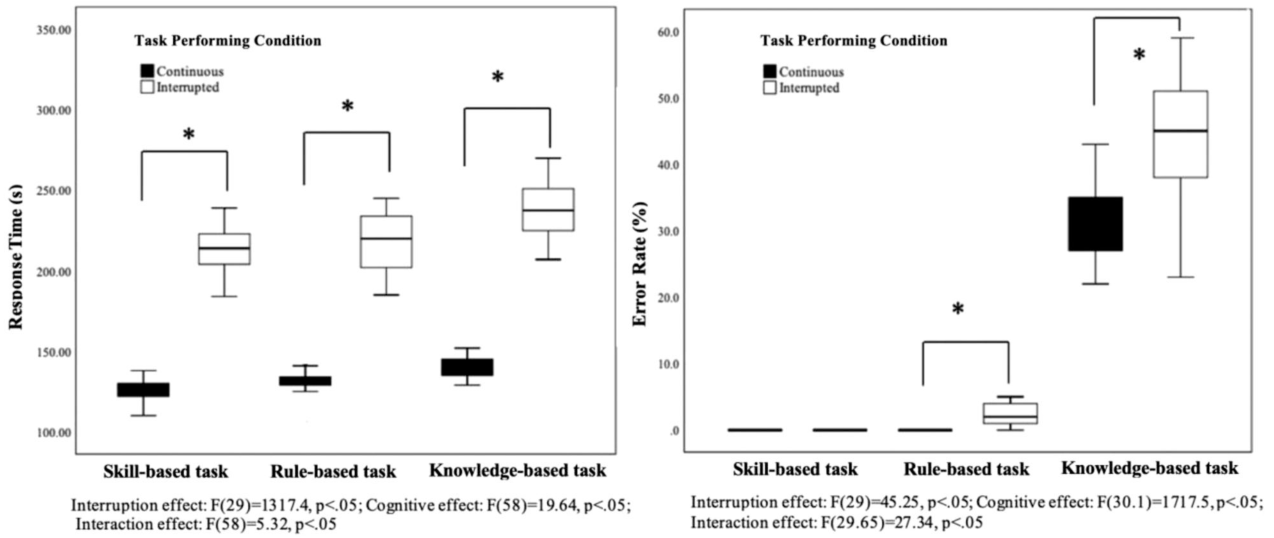

Figure 4. Comparison of primary task performance for 3 cognitive level tasks under 2 performing conditions.
Note. *Shows the significant paired *t*-test. The results of factors' effects (*f(df)*, *p*-value) are present under each diagram.

3.2. Primary task performance (TP)

The descriptive error rate and RT of the skill-, rule-, and knowledge-based tasks in the continuous and interrupted conditions are presented in Table 1.

The ANOVA test showed that there was a significant effect of factor TPC on RT and error rate with $F(1{,}29) = 1317.44$, $p < 0.05$, $\eta^2 = 0.978$, and $F(1{,}29) = 45.25$, $p < 0.05$, $\eta^2 = 0.609$, respectively. It also showed a main effect of factor TCL on RT and error rate with $F(2,\ 58) = 19.64$, $p < 0.05$, $\eta^2 = 0.606$, and $F(1.03,\ 30.10) = 1717.5$, $p < 0.05$, $\eta^2 = 0.983$, respectively. There was a significant interaction between factor TPC and factor TCL on RT and error rate with $F(2,\ 58) = 5.32$, $p < 0.05$, $\eta^2 = 0.155$, and $F(1.02,\ 29.65) = 27.34$, $p < 0.05$, $\eta^2 = 0.485$.

Figure 4 shows that the participants were more accurate and responded faster in the continuous condition than in the SM interrupted condition. Additionally, the paired t-tests showed that there were significant differences in RT and error rate between the continuous and interrupted conditions for the rule-based task ($t(29) = -26.93$, $p < 0.05$; $t(29) = -7.69$, $p < 0.05$) and knowledge-based task ($t(29) = -22.04$, $p < 0.05$; $t(29) = -5.72$, $p < 0.05$). But for the skill-based task, there was a significant difference only for RT between the continuous and interrupted conditions ($t(29) = -15.05$, $p < 0.05$), and there was no significant difference for error rate.

Furthermore, Figure 4 suggests that the RT and error rate of the knowledge-based task were higher than that of the skill-based and rule-based tasks in both the continuous and interrupted conditions. Also, it presents that the RT and error rate of the rule-based task were higher than that of the skill-based only under the interrupted condition. The paired comparisons showed that under the interrupted condition, the RT and error rate of the knowledge-based task were higher than those of the rule-based task ($t(29) = -4.11$, $p < 0.05$; $t(29) = -25.76$, $p < 0.05$), and higher than those of the skill-based task ($t(29) = -1.45$, $p < 0.05$; $t(29) = -28.19$, $p < 0.05$), and those of the rule-based task were higher than those of the skill-based task ($t(29) = -3.91$, $p < 0.05$; $t(29) = -7.69$, $p < 0.05$). Also, under the continuous condition, the RT and error rate of knowledge-based task were higher than those of the rule-based task ($t(29) = -5.96$, $p < 0.05$; $t(29) = -23.90$, $p < 0.05$), and higher than those of the skill-based task ($t(29) = -2.66$, $p < 0.05$; $t(29) = -23.90$, $p < 0.05$), but there was not a significant difference of the ones between the rule-based task and skill-based task ($t(29) = -0.316$, $p = 0.775$).

Table 2. The mean and SD of physiological indexes evoked by different tasks.

	Tasks under continuous condition						Tasks under interrupted condition					
	Skill-based		Rule-based		Knowledge-based		Skill-based		Rule-based		Knowledge-based	
Indexes	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*
HR	75.00	2.27	75.74	2.24	75.77	2.87	79.25	1.4	79.59	.5	79.88	.75
LF/HF	4.96	.85	5.85	.98	6.44	.50	7.44	.51	8.37	.49	10.51	.50
SC	4.39	.49	4.71	.46	5.50	.50	7.60	.49	7.89	.87	8.46	1.23
SDNN	63.92	1.77	63.85	2.03	63.00	2.09	63.29	1.87	63.00	1.68	62.92	1.79

Note. HR: heart rate (bpm); LF/HF: low frequency/high frequency; SC: skin conductance (μS); SDNN: SD of normal to normal (ms).

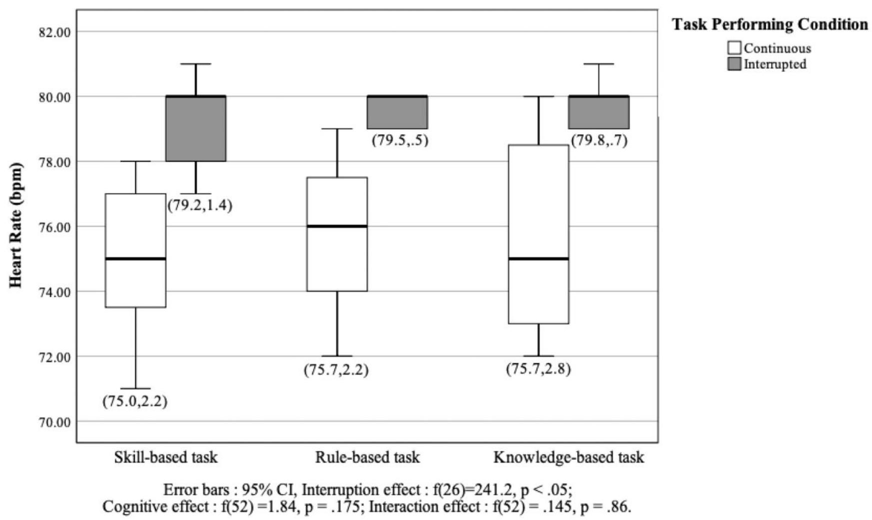

Figure 5. Comparison of heart rate evoked by 3 cognitive level tasks under 2 performing conditions.
Note. The results of factors' effects (*f*(*df*), *p*-value) are present under the diagram.

3.3. Physiological results

A summary of the descriptive statistics for the physiological indexes is shown in Table 2. Then, the physiological measures were subjected to ANOVA to test the differences under different conditions.

3.3.1. ECG activity

Three participants were excluded from the analysis due to poor-quality recordings. The repeated-measures two-way ANOVA results of HR showed that there was a significant main effect of TPC with $F(1, 26) = 241.258$, $p < 0.05$, $\eta^2 = 0.903$, but no significant main effect of TCL ($p = 0.175$) and no significant interaction ($p = 0.866$). The paired sample *t*-test showed that the interrupted tasks for three cognitive tasks (skill-, rule-, and knowledge-based) evoked higher HR than did the continuous tasks ($t(26) = -7.87$, $t(26) = -8.52$, $t(26) = -7.54$, $p < 0.05$). Moreover, the HR of the interrupted knowledge-based task was nearly significantly higher than that of the skill-based with $t(26) = -2.049$, $p = 0.051$, but there were no significant differences between other tasks. The HR changes under different conditions for three cognitive tasks are shown in Figure 5.

Figure 6 shows that SDNN decreases during the interrupted tasks and is also seen lower of the knowledge-based task than that of the rule- and skill-based tasks, and the SDNN of the skill-based task is lower than that of the rule-based task under both the continuous and interrupted conditions. However, the repeated-measures two-way ANOVA results of SDNN showed the main effects of factors TPC and TCL did not reach significance with $F(2, 52) = 1.427$, $p = 0.249$, $\eta^2 = 0.052$, and $F(1, 26) = 3.326$, $p = 0.080$, $\eta^2 = 0.113$. No significant interactions between TPC and TCL were found ($F(2, 52) = 0.883$, $p = 0.420$, $\eta^2 = 0.033$). The paired *t*-test showed that under the continuous condition, the knowledge-based task evoked lower SDNN than the rule-based task with $t(26) = 2.335$, $p < 0.05$, and the comparison between the continuous and interrupted tasks showed there was nearly significant difference only in rule-based tasks ($t(26) = 1.969$, $p = 0.06$), but no significant differences between other tasks.

The repeated-measures two-way ANOVA results of LF/HF showed that there were significant effect of

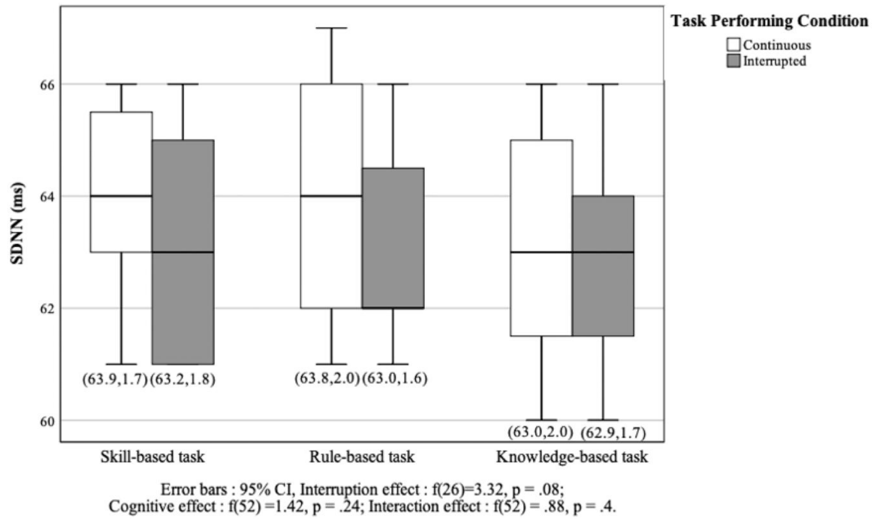

Figure 6. Comparison of SDNN evoked by 3 cognitive level tasks under 2 performing conditions.
Note. The results of factors' effects (*f*(*df*), *p*-value) are present under the diagram.

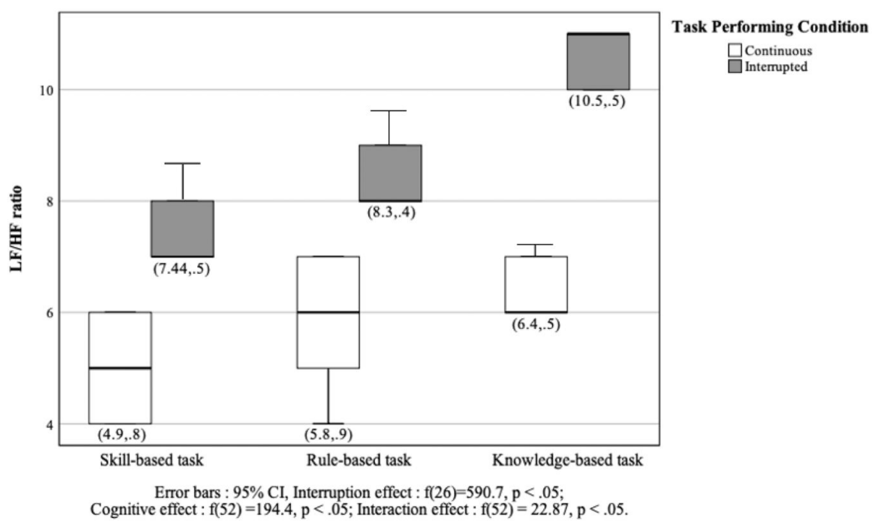

Figure 7. The comparison of LF/HF ratio evoked by 3 cognitive level tasks under 2 performing conditions.
Note. The results of factors' effects (*f*(*df*), *p*-value) are present under the diagram.

factor TPC with $F(1,\ 26) = 590.708$, $p < 0.05$, $\eta^2 = 0.958$, and significant effect of factor TCL with $F(2,\ 52) = 194.459$, $p < 0.05$, $\eta^2 = 0.882$, and significant interaction $F(2,\ 52) = 22.873$, $p < 0.05$, $\eta^2 = 0.468$. The paired *t*-test showed that the interrupted performing condition for the three cognitive tasks (skill-, rule-, and knowledge-based) evoked higher LF/HF than the continuous condition. Also, the comparison between different cognitive level tasks (skill-, rule-, and knowledge-based) showed that under the continuous and interrupted performing conditions, the knowledge-based task evoked higher LF/HF than did rule- and skill-based tasks, and rule-based task evoked higher than skill-based tasks. The changes of LF/HF under different performing conditions for three cognitive level tasks are shown in Figure 7.

3.3.2. Electrodermal activity

Data of two subjects were deleted due to the poor quality of signals during the experiment. The repeated-measures two-way ANOVA results showed that there was a significant main effect of factor TPC with $F(1,\ 27) = 672.492$, $p < 0.05$, $\eta^2 = 0.961$, and a significant main effect of factor TCL with $F(2,\ 54) = 37.58$, $p < 0.05$, $\eta^2 = 0.582$. There was no significant interaction between the two factors ($p = 0.693$). The paired t-test showed that the interrupted performing condition for the three cognitive level tasks (skill-, rule-, and knowledge-based) evoked higher mean SC than the the continuous tasks. Moreover, the paired comparisons showed that under the continuous performing condition, the mean SC of the knowledge-based task was

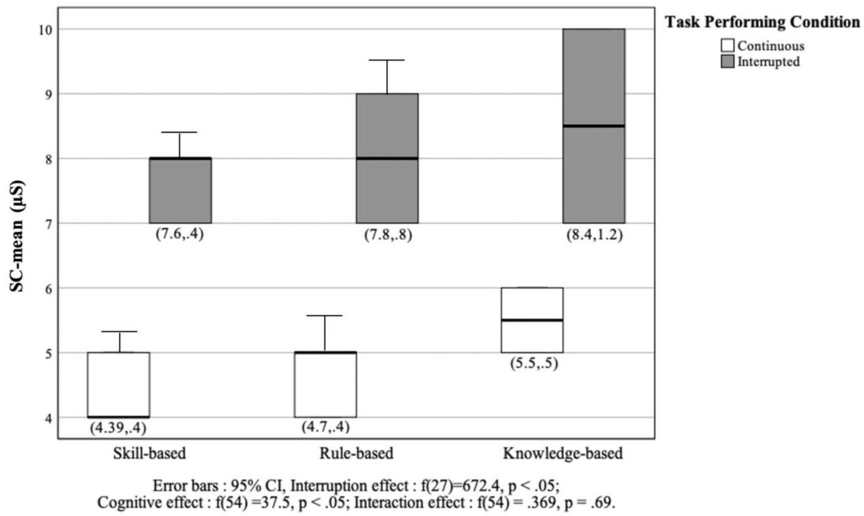

Figure 8. Comparison of SC-mean evoked by 3 cognitive level tasks under 2 performing conditions.
Note. The results of factors' effects (*f*(*df*), *p*-value) are present under the diagram.

higher than that of the rule- and skill-based tasks with $t(27) = -6.05$, $p < 0.05$ and $t(27) = -8.54$, $p < 0.05$, and the mean SC of the rule-based task was higher than that of the skill-based task with $t(27) = -2.78$, $p < 0.05$. Under the interrupted performing condition, the mean SC of the knowledge-based task was higher than that of the rule- and skill-based tasks with $t(27) = -2.161$, $p < 0.05$ and $t(27) = -3.11$, $p < 0.05$, but there was no significant difference for rule-based task and skill-based task ($p = 0.147$). The variations of the mean SC under the two performing conditions for the three cognitive level tasks are shown in Figure 8.

4. Discussion

This study aimed to evaluate the impacts of SM interruptions on the office workers' MWL and illustrate the role of information processing levels. In the modern workplace, interruption is a pervasive phenomenon in human-computer interaction. Mobile technologies have dramatically increased the number of interruptions, especially during work hours. Human brains may need about 23 min to resume tasks after getting interrupted (Mark, Iqbal, and Czerwinski 2017). A few studies investigated the effect of interruptions on the MWL (Midha et al. 2021; van Der Kleij, Hueting, and Schraagen 2018). This paper reports experimental results related to MWL while performing the simulated-computer tasks. The statistical analysis showed that using SM and manipulating the type of cognitive load impacted the MWL. These findings were supported by results on the subjective-, performance-, and physiological-based workload measures.

Our primary goal was to investigate whether interruptions of SM change MWL and aim to enable employees and managers to better control the dark side of SM interruptions at work. The results show that participants felt more workload under the interrupted condition and performed less accurately and slower than that under continuous one. This finding is consistent with the results of the previous studies showing increased resumption lags after interruptions (van Der Kleij, Hueting, and Schraagen 2018; Midha et al. 2021; Monk et al. 2004; Trafton et al. 2003). If we consider this in relation to the spare capacity (Sharples and Megaw 2015), as the interrupted condition was subjectively rated as requiring more MWL, there might be insufficient cognitive resources available to take on the interrupted task. This means that responding to the interruptions increased mental demand and hence MWL.

In terms of the effect of SM interruptions on physiological measurements, this study found that there were main effects of interruptions on HR, LF/HF, and SC metrics except for SDNN. One explanation for this pattern of results could be that SDNN focuses on the overall changes of HRV (Heart Rate Variability) within a longer time period (e.g. an hour) (Feng et al. 2021). As shown, there was more cardiac activity (ECG) during the interruption task compared to the continuous task, and this was significant for both HR and LF/HF signals. In other words, the LF/HF and HR values both increased during interrupted tasks, which were supported by the results of previous studies. Various literature found that higher HR and HRV were evoked with increasing task demands (De Rivecourt et al. 2008) and has been seen to increase under multi-task conditions (Fournier, Wilson, and Swain 1999) or when additional memory load is introduced (Finsen et al. 2001). Also, it was seen that NN (Normal to Normal) intervals decreased during a high-demand multi-attribute task in comparison to a low-demand task (Fairclough, Venables, and Tattersall 2005). Moreover, SC increased with the presentation of SM interruptions. This is consistent with the result of a prior study (Collet, Salvia, and Petit-Boulanger 2014), which showed that the electrodermal activity (EDA) was sensitive to the sudden stimulus.

Our finding shows that SM interruption is accompanied by changes in physiological activity indicators of MWL along with task demands increasing during different cognitive tasks. These changes could happen due to the human's limited cognitive and attention resources, especially when the resources are not well allocated across multiple tasks (Alm and Nilsson 1995; Card, Moran, and Newell 1983). Indeed, after interruptions, participants must remember the previous goal and task state so as being able to continue the suspended task. Moreover, in this experiment, subjects were asked to complete different cognitive tasks accurately to their best effort and accordingly this brought stress. If the cognitive tasks demand extensive resources (such as knowledge-based tasks) and need to be carried out for an uninterrupted interval, then it is possible that these tasks with interruptions would persuade stress (Hancock and Warm 1989; Warm, Parasuraman, and Matthews 2008).

One of the interesting findings of this experiment was the significant differences in some physiological responses between different cognitive level tasks (skill-, rule-, and knowledge-based). As ANOVA results showed, there were main effects of TCL on ECG (i.e. LF/HF) and EDA (i.e. SC) indexes, and these effects during interrupted tasks were more profound. However, for ECG indexes, HR and SDNN did not return the expected results. Previous studies have found that increasing task demands are not accompanied by changes in HRV if the manipulation impacts only structural or computational structures in the human information processing system (Jorna 1992; Mulder, de Waard, and Brookhuis 2004). In this regard, the human information processing levels seem not to differ considerably, particularly between the skill-based and rule-based task levels.

The observed physiological responses (LF/HF and SC) illustrated that the knowledge-based task posed more MWL than the other two task types (the skill- and rule-based tasks), especially under the interrupting condition. The reason may be that HRV increases during tasks requiring problem-solving compared to tasks requiring logical completion of a series of elements (Sosnowski, Krzywosz-Rynkiewicz, and Roguska 2004). Also, Miyake et al. (2009) found that EDA correlated with task difficulty during multiple tasks; in this regard, skin conductance level increased significantly during knowledge-based tasks compared to skill- and rule-based tasks.

Moreover, the obtained results have shown significant differences in the subjective rating of MWL and primary task performance between the three cognitive load levels. RT and error rate of the knowledge-based task was higher than skill- and rule-based tasks, and the rule-based task was higher than skill-based. However, there was no significant difference for RT and error rate between skill-based and rule-based tasks under the continuous condition. Rasmussen (1983) theorised that cognitive complexity would increase from a skill-based task (a task with low complexity) to a knowledge-based task (a task with high complexity). Accordingly, the primary task performance, the perceived mental workload rating, and the physiological signals observed in this study indicated that the knowledge-based task posed more MWL than the other two types and rule-based tasks more than skill-based tasks. One possible explanation for the result is that the knowledge-based task was more resource-intensive from a cognitive perspective or that the skill- and rule-based tasks were indeed less complicated. Another potential explanation of the observed relationship of cognitive task complexity to workload response is that the rule- and skill-based training during orientation sessions was more effective than knowledge-based training.

Regarding our research question 3 (interaction effect between TPC and TCL), it was found that the perceived workload for interrupted tasks with high cognitive levels is more demanding. Participants perceived more mental effort during knowledge-based tasks than the rule- and skill-based tasks, and the interaction effects represented that the differences between cognitive task levels were more pronounced for interrupted tasks. Thus, in reality, SM interruptions during high load tasks at work may put more pressure on employees, and make them feel overloaded and result in behavioural and performance problems. On the other hand, the significant joint effects of SM interruption and cognitive task level express that the impact of SM interruptions at work on the primary task performance concurrently depends on the information processing level of ongoing tasks. As a result, employees' cognitive abilities are stretched when they confront so much information, which may lead to lower productivity.

In contrast, the interaction effects of SM interruption and cognitive task level on physiological measures (HR, SDNN, and SC) did not emerge. A possible reason may be the potential differential response of the human stress system(s). Stress is one important factor influencing the biological stress system-activity (Chrousos and Gold 1992; Chrousos 2009), and SM interruption is a potential digital stressor at work such as flooding text messages or emails (Gupta, Li, and Sharda 2013; Reinecke et al. 2017; Lindstrom 2020; Hefner and Vorderer 2016; Barley, Meyerson, and Grodal 2011). Although stressors, in principle, can induce physiological responses, it has been proposed that different types of stressors may trigger different stress physiological responses (i.e. specificity hypotheses, Becker et al. 2022). According to this hypothesis, the physiological reactions towards tasks and the nature of interruptions may vary based on different stress systems in the course of increased demands. Therefore, stress may have affected the results of this study, which is not considered in our analysis and may have led to non-significant interaction effects for physiological results. Furthermore, previous research has shown that stress activates the hypothalamus-pituitary-adrenocortical (HPA) axis, which controls various physiological processes, particularly the ECG and EDA indexes (Healey and Picard 2005; Sun et al. 2010); hence, the physiological responses may be affected.

4.1. Implications

This study provides some practical insights for organisations and employees on how to manage SM information interruptions in the workplace. First, office workers suffer from increased overall MWL when receiving frequent SM interruptions. Although office work requires less physical workload compared to many traditional production tasks, many office workers complain of neck and shoulder discomfort (cervicobrachial) (Leyman et al. 2004). Previous literature has linked these symptoms to MWL (Darvishi et al. 2016; Khandan et al. 2018). For example, Khandan et al. identified a significant relationship between musculoskeletal disorders (MSDs) in different parts of the body and MWL. In this regard, to decrease workload by SM interruptions, supervisors may need to seek other communication methods if immediate responses are not necessary. Also, organisations may need to monitor SM interruptions received by employees and establish policies or use technical approaches to control the frequency of SM interruptions. This could also be accomplished through the use of more advanced graphical interfaces. Human-computer interaction studies demonstrated that interruption is also a user interface design issue (McFarlane 2002). Interfaces of SM apps could be improved with added functionalities that support the multitasking work condition, such as embedded intelligent functions to support the post-interruption period (recovery phase) and arranging the SM interruption based on who the sender is (Gupta, Li, and Sharda 2013).

Second, this study provides the first empirical evidence on the important role of the factor TCL in the effect of SM interruptions on MWL, in addition to another joint study reported in Zahmat Doost and Zhang (2022), and Midha et al. (2021). The impact of SM interruption on MWL is aggravated during tasks that involve higher-level aspects of cognition (knowledge-based task) than lower-level (skill- and rule-based tasks). Office workers need to receive training on how to turn off the status awareness function to set their status on SM according to the complexity of their ongoing tasks and use the proper SM manner. Companies could reduce interruptions with opportunities to expand employees' autonomy and discretion to block off instant alerts during cognitively demanding tasks. These interventions need organizational-level agreements and changes in personal habits and work norms. Unfortunately, it is possible but hard to sustain (Perlow 1999). Also, the effects of SM interruptions during demanding tasks could be overcome by building a plan as "Ready to Resume", that is, employees plan their return to the ongoing task before switching to the intruding demand (e.g. pre-determine the specific intervals for answering coworkers' inquiries or relaxing through SM applications) (Leroy and Glomb 2018). The authors found that engaging in such a plan helps reduce attention resuming and improve performance on the interrupting task. Moreover, this could be achieved by building functions at either the employees or the management side that control SM flow based on who the sender is and when. For example, during complex tasks that need uninterrupted time, set up a filtering function to show the necessary SM notifications or messages that are promptly displayed at the top.

Third, previous research about the effect of SM has been conducted using subjective measurements; this study took place in a laboratory environment and used behavioural and physiological methods to detect the variations of MWL. Therefore, this study can be considered as a stepping stone between strictly controlled laboratory research and unconstrained research in the real world, and the findings can guide progressing studies into the workplace.

4.2. Limitations and future studies

Despite the conclusions stated above, this work has the following limitations. The study was conducted in a laboratory, and the experimental conditions were attentively controlled. Unlike manipulating information processing under simulated tasks, it is hard to recognise task demand in the real environment, and the actual environment will also affect the physiological signal assessment. This means that the process and conclusions should be extended to occupational settings with caution. Moreover, other variables may underestimate actual responses when being interrupted during work, such as personality and self-discipline, which can be considered in future research. From an individual difference perspective, higher working memory capacity (WMC) reduces resumption lags (Foroughi et al. 2016).

Also, due to our experiment design, we cannot exclude the potential differential response of the human stress system(s) towards task types and interruptions (Becker et al. 2022). Different interruptions may have different effects on physiological responses (LF/HF and SC) based on different stress systems responding in the course of increased demands. For example, social interruptions (i.e. party invitation) may be inflated by potential self-evaluation threats that are usually associated with a strong physiological stress response compared to potential challenging HPA axis task triggers (Dickerson, Gruenewald, and Kemeny 2004). Therefore, in future studies, it might be of interest to consider the types of interruptions (Chen and Karahanna 2018; Becker et al. 2022) with potentially different effects for employee well-being and performance outcomes in real-world office environments.

We randomly selected individuals with practical experience in office work as our sample. Since the data collection was performed only in Chinese, specific characteristics of Chinese and their habit in dealing with SM use may limit this study's generalisability and external validity (Peng, Wang, and Chen 2019). Further study can address this issue by comparing results based on samples from different countries and cultures. In addition, since there are heterogeneities in different industries, it will be an interesting direction to take the methods in this study and apply to other work environments.

5. Conclusions

This study evaluated the impact of SM interruption and cognitive load level in office-like tasks on MWL, addressing gaps in SM research and practical knowledge about the role of SM interruptions in the workplace. It is found that the information processing level of primary tasks (skill-, rule-, and knowledge-based tasks) is essential and could influence task performance and MWL. This conclusion was supported by consistent results on subjective rating, primary task performance, and physiological signals related to MWL measures. The results may help individuals to understand the effect of interruption on MWL levels during different cognitive load tasks and could lead to further aid in improving their working habits.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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