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Influence of automation on mind wandering frequency in sustained attention

Jonas Gouraud[a,*], Arnaud Delorme[b,c], Bruno Berberian[a]

[a] System and Information Processing Department, ONERA, Salon de Provence, France
[b] Brain and Cognition Research Center (Centre de Recherche Cerveau & Cognition) (UMR 5549), CNRS, Toulouse, France
[c] Swartz Center for Computational Neurosciences, University of California, San Diego, CA, USA

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ABSTRACT

There is accumulating evidence which shows that mind wandering may be increased within automated environments. This is particularly concerning when considering the negative effect of mind wandering on short-term performance. Seventeen participants performed an obstacle avoidance task under two conditions, manual and automated, each lasting 40 min. Subjects perceived the manual condition as more demanding than the automated one. We noted a significant increase of mind wandering frequency after only approximately 20 min under the automated condition. While learning and workload alone cannot explain these results, more automation-related phenomena, such as complacency or loss of agency, could play a role. Pupil diameter decreased during mind wandering compared to focus periods, revealing a decoupling from the task. The decrease remained stable in amplitude across different times and conditions. Research on mind wandering could be used to characterize an operator's state of mind regarding issues related to system interactions.

1. Introduction

Mind wandering (MW) is a family of experiences relating to the mind's tendency to engage in thoughts unrelated to the here and now. It is a ubiquitous phenomenon that can be intentional or spontaneous (Golchert et al., 2016; Seli, Risko, & Smilek, 2016), guided or unguided (Smallwood, 2013), and may emerge when performing a task or at rest (Smallwood, Baracaia, Lowe, & Obonsawin, 2003). Its onset can be triggered by external information or generated internally (McMillan, Kaufman, & Singer, 2013; Smallwood & Schooler, 2006). In the following paper, we have focused on task-unrelated MW without discriminating other dimensions. Task-unrelated MW is more likely to occur in monotonous environments (Eastwood, Frischen, Fenske, & Smilek, 2012), or when operators perform familiar (Bastian et al., 2017) or long term tasks (Smallwood & Schooler, 2015). These task features often define modern automated environments. In this context, we aim to explore how our technological environment impacts the occurrence of such phenomena.

Critically, MW is known to favor a decoupling from the ongoing task at perceptual and stimulus-processing levels (Kam et al., 2012; Schooler et al., 2011). Oculometric studies indicate that MW disrupts visual information flow by reducing pupil diameter (McIntire, McIntire, Mckinley, & Goodyear, 2014; Smallwood et al., 2011) and increasing blink frequency (Smilek, Carriere, & Cheyne, 2010). Neuronal studies also demonstrated an increase in alpha wave power in the occipital scalp (linked to sensory inhibition; Foxe & Snyder, 2011) during MW episodes during a visual task (O'Connell et al., 2009). At the same time, Event-Related

* Corresponding author at: ONERA, Salon de Provence, 13661, Salon Air, France.
E-mail address: contact@jonasgouraud.com (J. Gouraud).

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Potentials linked to external information perception and processing exhibited a lower amplitude (Smallwood, Beach, Schooler, & Handy, 2008).

At the behavioral level, MW decoupling translates into a decrease in performance. Reaction times exhibit higher variability (Bastian & Sackur, 2013), while omissions and anticipations are more common (Cheyne, Carriere, Solman, & Smilek, 2011; but see Head & Helton, 2016 for the rationalization hypothesis). At the same time, multiple paradigms reveal a decreased accuracy during MW episodes (Kam et al., 2012). In simulators, Yanko and Spalek (2014) studied MW influence on driving performance; they observed longer reaction times to unexpected events, shorter headway distance and higher speed. Their results were corroborated by other studies in driving environments (Dündar, 2015; He, Becic, Lee, & McCarley, 2011; Lerner, Baldwin, Higgins, Lee, & Schooler, 2015). Because task-unrelated MW diverts operators' attention from their primary task and impacts human performance, its occurrence in an operational context appears to be a critical issue.

The issue is particularly important for critical system operators (pilots, nuclear plant operators or air-traffic controllers). In a modern setting, they are required to maintain sustained, focused attention for long periods of time in low probability environments. Multiple studies have shown that operators cannot achieve efficient supervision for hours at a time due to a vigilance decrement correlated with the length of time on the task (see the debate surrounding underload and overload theories; Fraulini, Hancock, Neigel, Claypoole, & Szalma, 2017; Gouraud, Delorme, & Berberian, 2017; Pattyn, Neyt, Henderickx, & Soetens, 2008; Thomson, Besner, & Smilek, 2016). This vigilance issue is perceived as a cause of the out-of-the-loop (OOTL) performance problem, a set of difficulties observed in automated environments which prevents the efficient supervision of automation (Amalberti, 1999). This analysis has been corroborated by operational reports. Mosier, Skitka, and Korte (1994), examined NASA's Aviation Safety Reporting System (ASRS) database and reported that 77% of the incidents involved an over-reliance on automation leading to a probable failure in attention or monitoring. Similarly, Gerbert and Kemmler (1986) studied German aviators' anonymous responses to questionnaires about automation-related incidents, and pointed out failures of vigilance as the largest contributor to human error.

However, although automation induces vigilance failure, its impact on MW remains unclear. We assume that supervising ultra-reliable systems would encourage operators to decrease cognitive resources allocated to the monitoring task. In that case, time saved by automation, which should normally be used for monitoring and planning, could instead be filled by task-unrelated MW. Operators experiencing MW would be unprepared to regain manual control over the system in response to rare critical events. Casner and Schooler (2013) studied the evolution of MW within a cockpit simulator. Experienced pilots were required to fly the approach of a busy New York airport, a procedure lasting 16 min. As in a real flight, they could choose which autopilot modes to turn on, and when. They observed more MW reports when pilots were not interacting with the system, and also when everything was going according to plan. However, they did not find any correlation between the automation level used and the frequency of the MW reports. Three different hypotheses could explain the absence of a significant influence of automation on MW: there may not be any link between MW and automation; sessions may not have been long enough to reveal the influence of automation; or pilots may have adapted their use of automation to their vigilance levels. The question of the link between MW and automation still remains to be answered.

We believe that automation might influence MW during longer sessions within ecological environments when operators cannot adapt the automation level. We think that this impact may be observable in the frequency as well as the oculometric markers of MW. Our experiment addresses these hypotheses.

2. Material and methods

2.1. Participants

Seventeen participants (five female) performed the experiment (ages ranging from 21 to 42; M = 27.3, SD = 6.0). We performed an *a posteriori* power analysis using η^2 reported by Unsworth and Robison (2016). This study was the only one, to our knowledge, to investigate MW and oculometry using linear models, which was our intention (see the *Data Analysis* subsection). They reported $\eta^2 = 0.32$ and $\eta^2 = 0.34$ for the influence of time over MW frequency and pupillometry respectively. Using the *pwr* function in R (Champely, 2017; R Core and Team, 2016), we calculated $N_{lim} = 15$ (i.e., we needed at least 15 participants) for standard values of $\alpha = 0.05$, $\beta = 0.80$ for two-tailed tests.

The participants enrolled in this study were volunteers from our company (ONERA, the French Aerospace Lab). All participants were unfamiliar with the concepts used in this study. They had normal or corrected-to-normal visual acuity. All participants signed a written declaration of informed consent. The protocol was approved by the ONERA organization and was conducted in accordance with the World Medical Association's Declaration of Helsinki.

2.2. Task

2.2.1. Environment

We used the LIPS (*Laboratoire d'Interactions Pilote-Système*, or Pilot-System Interaction Laboratory) environment, developed at ONERA, to program our experiment (see Fig. 1). An unmanned air vehicle (UAV), depicted as a plane seen from above, remained at the center of a 22-inch 2D radar screen, while travelling forward following waypoints arranged in a semi-straight line, and encountering clusters of obstacles along the way (every 45 s on average). Each cluster contained between one and five obstacles, including one on the trajectory. The participants were instructed to control the movements of the UAV to avoid the obstacles. The LIPS environment includes a physics engine to reproduce convincing *Rafale* aircraft motion behavior. The LIPS was displayed on a screen within the SIMPIT environment shown in Fig. 1.

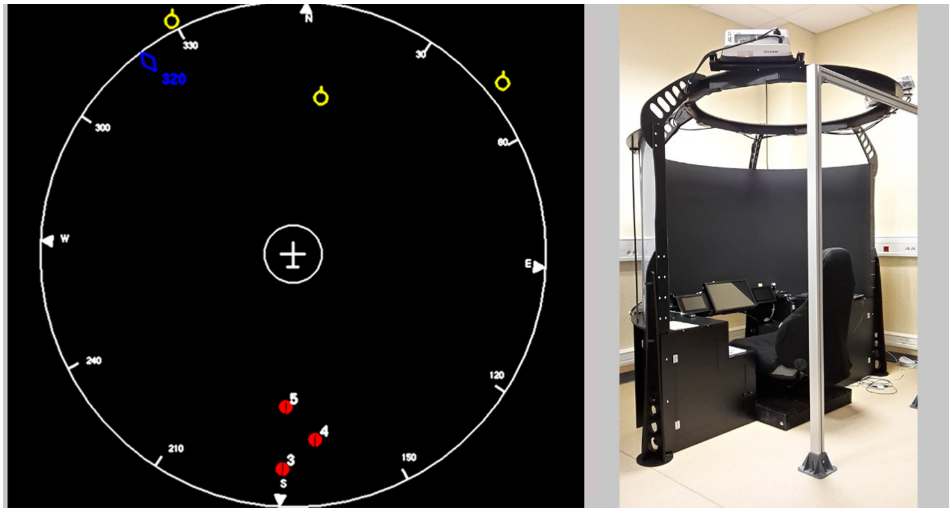

Fig. 1. Screenshot of the LIPS interface and the environment. One of the screens is used for the task and the other is used for the questionnaire probes. For the task, the plane at the center is static and the surrounding objects (yellow and red numbered symbols) are moving. During left and right avoidance maneuvers, the plane remains static while the background is rotated. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.2.2. MW probes

Python 3.6 was used to program the mental probes. On average every two minutes, the probe appeared on a secondary 10-inch screen next to the main screen. For technical reasons the obstacle avoidance task was not paused when the probe was displayed. Participants were asked to fill it in as soon as it appeared, and were told that any successful or failed trial during this interval would not be taken into account. Participants were informed that the probe was not part of the evaluation. This instruction was given to lower the impact of instructions on their natural propensity to mind wander. Participants were required to answer the following questions (originally in French, see Fig. 2): "When this probe appeared, what was your attention directed towards?" Possible responses were "Towards the task" (e.g., thinking about the next obstacle, the decision to make, the incoming waypoint), "Something related to the task" (e.g., thinking about performance, interface items, last trial), "Something unrelated to the task" (e.g. a memory, their last meal or a body sensation, hereafter defined as MW) or "External distraction" (e.g., conversation, noise). The preceding examples were given to participants to illustrate each category. We were primarily interested in "Towards the task" and MW reports. "Something related to the task" reports were integrated to the probes to avoid participants reporting MW when thinking about their performance (Head & Helton, 2016). Noises were integrated to avoid participants reporting MW if they were focused on any external signal.

2.2.3. Conditions

Two conditions were proposed. Firstly, under the "manual" condition, participants were asked to manually avoid obstacles. The system detected obstacles on the trajectory 13 s before impact, at which point an orange circle appeared around the UAV and the participant was required to initiate an avoidance maneuver. Participants were able to choose how to avoid the obstacle by clicking on "*Evitement Gauche*" (left maneuver) or "*Evitement Droite*" (right maneuver), which altered the trajectory of the UAV in the direction selected, following an angle automatically computed to avoid the obstacle (if possible). Each obstacle had a safe circle similar to that

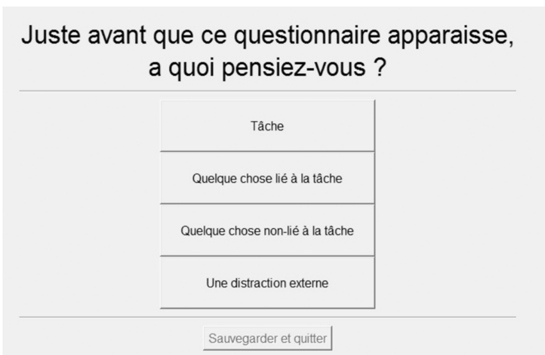

Fig. 2. Screenshot of one of the French MW probes. The question is "When this probe appeared, what was your attention directed towards?" Possible responses were "Towards the task", "Something related to the task", "Something unrelated to the task" or "External distraction".

of the UAV (see Fig. 1). A collision warning (i.e., an orange circle around both the UAV and the obstacle with the message "Collision") was displayed if the UAV safe circle penetrated the obstacle safe circle. A trial with a collision warning triggered was marked as failed. To resume the initial trajectory, the participants were required to click on the "*Retour trajectoire*" (return to original trajectory) button. If no action was taken within 16 s after the first change in trajectory, the aircraft automatically resumed the trajectory and the trial was marked as failed.

Secondly, under the "automated" condition, the participants were required to monitor the obstacle avoidance system. They were instructed to click an "*Acquittement*" (acknowledgement) button to acknowledge automated avoidance decisions as soon as they noticed them (twice per trial, once to acknowledge avoidance of the object and once to acknowledge the return to the normal trajectory after avoiding the object). A feedback message was displayed to the participants. The acknowledgement ensured that participants would have the same motor input under both the manual and automated conditions. If participants detected an automation error, i.e., choosing the wrong obstacle avoidance trajectory, they were instructed to click the button "*Changement d'altitude*" (change altitude) so that the UAV would perform an emergency descent. A feedback message was displayed in that case as well. The altitude change ensured that participants were facing a supervision task.

2.2.4. Procedure

Participants were explicitly instructed that detection accuracy was more important than speed of button clicks. In a counterbalanced approach, each participant performed the task under the two conditions on two separate days. Each day started with an explanation of the task, followed by a 10-minute training period and a 40-minute session under the respective conditions. Each session contained 60 clusters of obstacles. Each cluster was considered to be a trial. They were separated by intervals of 45 s on average. Twenty probes were encountered under each condition. The probe distribution was not correlated with events on the obstacle avoidance task in order to avoid performance influencing MW reports (Head & Helton, 2016). The automated condition included eight conflicts which were followed by a probe within a 10-second interval after the conflict. Participants encountered one system error (where they were required to click the "*Changement d'altitude*" button) during training, and another during the automated condition at the end of the third block. Under the manual condition, participants encountered, at the end of the third block, a conflict impossible to avoid. Both the automation error and this conflict were not followed by an attentional probe for at least 10 s afterwards.

2.3. Data recording

2.3.1. MW probes

Comma Separated Value (CSV) text files were used to store all answers. The exact appearance time was saved along with each answer, in order to synchronize probe data with the pupillometric signal.

2.3.2. Post-task questionnaire

We used a validated French version of the NASA Task Load Index (TLX) questionnaire to evaluate task load (Cegarra & Morgado, 2009; Hart & Staveland, 1988). This questionnaire includes questions pertaining to mental demand, time pressure, physical strain, effort, frustration, and perceived performance. Participants were asked to answer each question on a scale ranging from 0 to 20. We were primarily interested in the "mental demand" dimensions for two reasons. First, attempting to measure "workload" or "task load" is hazardous, since the terms themselves are open to criticism (Dekker & Hollnagel, 2004). Second, we wanted to focus on this term as an important one in the underload–overload debate (Pattyn et al., 2008; Warm, Parasuraman, & Matthews, 2008). Each participant filled in two TLX questionnaires (one after each session). Although a TLX questionnaire completed at each block would allow precise workload monitoring, we believe that MW would have been artificially lower due to the interruption in the task. For this reason the TLX was only filled in at the end of each session.

2.3.3. Oculometry

Oculometric data were recorded using the hardware SmartEye Pro 3.0 and the software SmartEye 6.2.4. The system included 2 infrared illuminators and 3 cameras (120 Hz) placed above the screen to avoid any direct contact with the participant (see Fig. 1). Gaze calibration was performed using a 4-point grid. SmartEye software gave an average of both pupil diameters. When only one eye was available, this pupil was used and the software indicated a degraded quality of measurement.

2.4. Data analysis

2.4.1. MW probes

Participants' clicks and probe answers were saved in CSV text format. We used R-Studio and R 3.4.1 (R Core and Team, 2016; RStudio Team, 2015) to analyze the data.

2.4.2. Oculometry

The 10 s preceding each probe were extracted from oculometric data. This period length is in line with the literature investigating MW and oculometric markers (Bixler & D'Mello, 2014, 2015; Franklin, Broadway, Mrazek, Smallwood, & Schooler, 2013; He et al., 2011). Extracts before "Towards the task" and "Something related to the task" were classified as "Focus" to avoid any influence of poor performance on mind wandering related measures (Head & Helton, 2016). Extracts before "Something unrelated to the task"

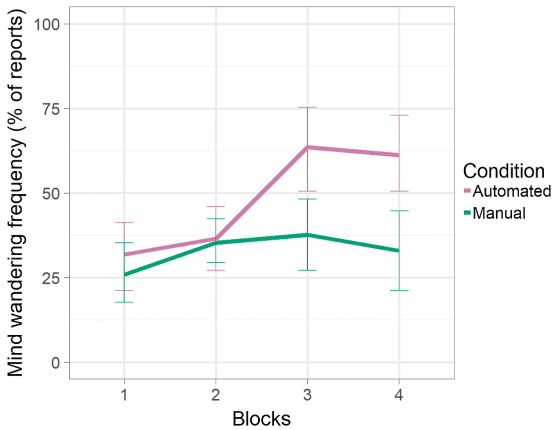

Fig. 3. MW frequency evolution under each condition. Error bars show the 95% confidence intervals based on bootstrapping.

were classified as "MW". Extracts before "External distraction" were discarded, since we were interested in attention focused on the task or internally. We performed filtering on pupillometry using the R package reshape (Wickham, 2007), psych (Revelle, 2017), ggplot2 (Wickham, 2009, p. 2) and robfilter (Fried, Schettlinger, & Borowski, 2014). Filtering was done in two passes, following a method already used in the literature (Grandchamp, Braboszcz, & Delorme, 2014). Firstly, we filtered the signal. Pupil diameter had to be between 1 and 10 mm (due to the physical limits of the pupil diameter, see (Lemercier, 2014), which had to be less than 80% different from the preceding value (due to pupil dynamic limits) and had to be of a quality (computed by the SmartEye software) over 0.01. Extracts were discarded if their resulting pupil diameter series consisted of less than 70% compliant values. The proportion of extracts excluded due to low quality (9.6%) is in line with that excluded in other investigations (Smallwood et al., 2011). Resulting extracts were completed using basic linear interpolation. A second filtering pass was applied with a median filter (moving window of 50 frames). We also discarded all epochs that included some actions from participants during the interval (i.e., if participants clicked on a button during the 10 s). This ensured that all epochs did not include phasic activity linked to decisions (which could mask MW influence).

Fixations, saccades and blinks were computed by the SmartEye Pro software. Blinks were computed using sliding windows of 700 ms. Saccades were defined in SmartEye Pro parameters as gaze velocity over 35 deg/s. Saccades were limited to 200 ms. Fixations were frames where the gaze velocity remained below 15 deg/s.

3. Results

3.1. Mind wandering frequency

We split the 40-min sessions into four blocks lasting approximately 10 min and containing five reports each. MW propensity was calculated as a percentage of all reports in the block (see Fig. 3). Participants reported MW episodes for almost half of the probes ($M = 49\%$, $SD = 30\%$). This rate is consistent with previous studies on the subject (Kam et al., 2011; Smallwood & Schooler, 2006, 2015). Each participant reported on average 4% "external distraction" thoughts in each session ($SD = 5\%$). We did not include these reports in the subsequent analysis, since we were interested in attention focused on the task or internally.

We used the *ezANOVA* function (Lawrence, 2016) to perform a two-way repeated measure ANOVA. We entered time (block) and level of automation (condition) as independent variables. We used the MW frequency as a dependent variable. Mauchly's test indicated that the assumption of sphericity had not been violated for the main effect of block, $W = 0.64$, $p = .251$, and block × condition, $W = 0.90$, $p = .906$. There were significant main effects of time over the MW frequency, $F(3, 48) = 8.88$, $p < .001$, $\eta_G^2 = 0.14$ (Generalized Eta Squared, Bakeman, 2005; Olejnik & Algina, 2003), as well as of the level of automation over the MW frequency, $F(1, 16) = 12.67$, $p = .003$, $\eta_G^2 = 0.11$. There was also a significant interaction effect between the length of time and the level of automation, $F(3, 48) = 5.22$, $p = .003$, $\eta_G^2 = 0.07$. Without specific *a priori* predictions on the evolution of MW frequency over time, we conducted Tukey's post-hoc tests on the model, including the Block variable for each condition separately. We used the *glht* (Hothorn, Bretz, Westfall, Herberger, M. R., & Schreibe, 2017) and *mes* (AC Del Re, 2014) functions. For the manual condition, all differences were non-significant ($p > .366$). For the automated condition, the third and fourth blocks had significantly higher MW frequency compared to the first block, $p = .001$, $d = 0.54$ and $p = .003$, $d = 0.32$, respectively. Similarly, Blocks 3 and 4 had significantly higher MW frequency compared to Block 2, $p = .007$, $d = 0.12$ and $p = .016$, $d = 0.12$, respectively.

3.2. NASA TLX scores

Each participant filled in two TLX questionnaires (one after each session). The mean score for mental demand for each subject (see Fig. 4) varied substantially (ranging from 1 to 14, $M = 6.50$, $SD = 3.96$). Shapiro-Wilk's test indicated that the assumption of normality had been violated for the TLX values, $W = 0.918$, $p = .015$. Therefore, we used Wilcox's robust version of the t-test proposed

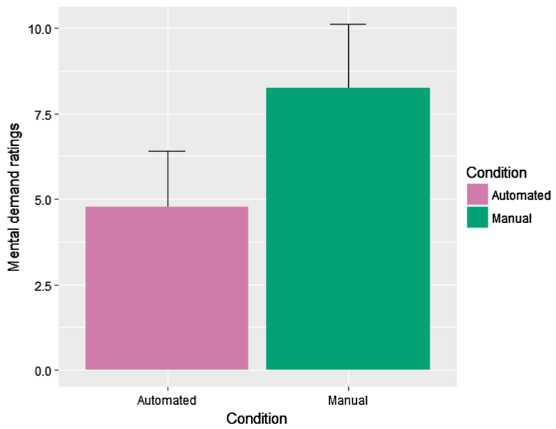

Fig. 4. Mental demand ratings for each condition. Error bars show the 95% confidence intervals based on bootstrapping.

in the WRS2 package (Mair, Schoenbrodt, & Wilcox, 2017). On average, participants perceived that the automated (M = 4.76, SD = 3.17) condition required less cognitive resources than the manual (M = 8.23, SD = 3.99) condition, $t(10)$ = -3.35, p = .007, d = 0.78. Ratings show that our automated condition succeeded in lowering mental demand.

3.3. Oculometry

3.3.1. Influence of MW over oculometric measures

Epochs discarded because of participant actions involved eight reports under the automated condition and nine under the manual condition (see supplementary materials for figures). We plotted pupil diameter during the 25 s preceding reports (Fig. 5). This confirmed that our 10-second interval was appropriate.

We used the *lme* function (Pinheiro, Bates, DebRoy, Sarkar, & R Core Team, 2017) to perform a linear mixed-effect analysis despite missing values ("external distraction" reports and bad quality extracts excluded). We chose this function since it has been widely used in the literature of mixed-effect models and the R statistical package handles a wide range of data structures (Field, Miles, & Field, 2012). As random effects, we had intercepts for subjects, as well as by-subject random slopes for the effect of condition (no other random slope due to convergence problems of the model). Visual inspection of residual plots did not reveal any obvious deviations from normality or homoscedasticity. P-values were obtained by likelihood ratio tests using ANOVA on the full model against the models with no fixed effect, with only block, with block and condition, and with block and condition and their interaction. We reported generalized eta squared (η_G^2) for effect size. This metric provides comparability across between-subject and within-subject designs (Bakeman, 2005; Olejnik & Algina, 2003). We used the *aov_car* function of the *afex* package (Singmann, Bolker, Westfall, & Aust, 2018) to compute generalized eta squared. The results are shown in Table 1. On average, participants showed a significantly smaller pupil during MW episodes (see Fig. 4). There was no significant effect of MW on other markers.

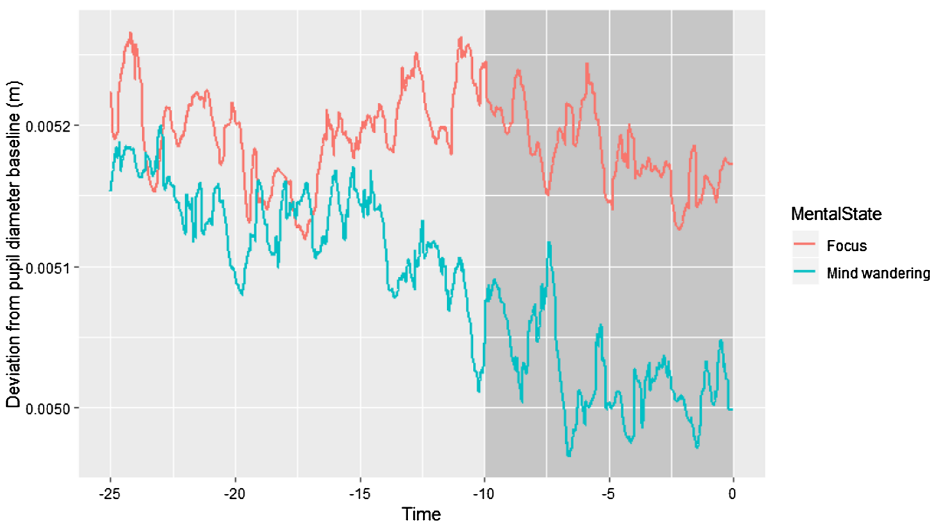

Fig. 5. Pupil diameter evolution during the 25-second interval preceding the probe display. The grey section is used for computation.

Table 1
Comparison of oculometric measures during MW and focus episodes. Bolded values are significant.

Parameter	MW values		Focus values		Attentional State model		
	M	*SD*	*M*	*SD*	$\chi 2(1)$	*p*-value	η_G^2
Pupil size (mm)	5.00	0.67	5.18	0.79	**5.01**	**0.025**	**0.010**
Saccade frequency (sacc/s)	3.95	2.43	3.70	2.32	0.28	0.600	0.002
Mean fixation duration (s)	0.29	0.75	0.39	0.83	0.64	0.423	< 0.001
Blink frequency (blink/s)	0.07	0.12	0.06	0.11	2.69	0.101	0.020

3.3.2. Influence of time and automation on oculometric differences

We looked for any influence of time or automation on oculometric markers. We used the *lme* function to perform the linear mixed-effect analysis. As fixed effects, we entered time (block), level of automation (condition) and their interaction. As random effects, we had intercepts for subjects, as well as by-subject random slopes for the effect of block and condition (no other random slope for convergence problems). Visual inspection of residual plots did not reveal any obvious deviations from normality and homoscedasticity. η_G^2 could not be computed for the interaction model due to an uneven number of reports in each block (rejected data during filtering). Results are displayed in Table 2. Oculometric markers remained stable through time and condition.

4. Discussion

We studied the impact of automated compared to manual environments on MW and its behavioral and oculometric markers. The automated condition revealed significantly lower TLX scores compared to the manual condition, showing a protocol in line with the usual goals regarding automation introduction (Wiener, 1988). Three main results have been shown: (1) MW increases after some time has elapsed in an automated environment, (2) there is a difference in pupil diameter between MW and focus episodes but not for other oculometric markers and (3) pupillometric difference between attentional states remains stable across times and conditions. We discuss these results below.

4.1. MW frequency

The first result is a significant increase in the MW frequency under the automated condition between Blocks 2 and 3. No significant time-related evolution of MW was observed under the manual condition. Since both conditions lasted the same amount of time, contained a similar number of actions and pursued the same goal (avoid incoming obstacles), time-related phenomena (drowsiness, habituation, or tiredness) cannot entirely explain the fact that MW increased only under the automated condition. Similarly, the level of automation alone cannot explain the observed data, since the trend did not evolve linearly with time-on-task and showed no difference between conditions for the first two blocks (task complexity remained constant throughout each condition). Finally, since we only took intervals without actions, the MW report difference could not have been biased by a desire to justify low performance (Head & Helton, 2016).

On the one hand, the absence of MW increase under the manual condition is interesting, considering the well-established vigilance decrement observed during sustained attention (Cabon, Coblentz, Mollard, & Fouillot, 1993; Davies & Parasuraman, 1982; Jeroski, Miller, Langhals, & Tripp, 2014; Mackworth, 1948). Moreover, multiple previous studies exist showing an increase of MW frequency with time (McVay & Kane, 2012; Thomson, Seli, Besner, & Smilek, 2014; Unsworth & Robison, 2016). An explanation may lie in the difference between our protocol and traditional protocols studying mind wandering. Studies reported mostly GO/NOGO and reading tasks. GO/NOGO tasks use frequent stimuli to determine how mechanical behavior induced by MW could affect performance. These tasks have low-complexity. Participants quickly realize how much cognitive resource to put into the task and become rapidly familiar with stimuli. The second common task, reading, forces participants to be active and read the given text. It is a familiar activity for most subjects. Unlike for the GO/NOGO and the reading task, participants in our experiment were completely unfamiliar with the LIPS. Trials were extensive (at least 40 s per trial), which also contributed to the impossibility of the task becoming familiar within a few minutes.

Table 2
Influence of time and condition over the oculometric marker difference between attentional states.

Parameter	Time model			Time + Condition model			Time * Condition model		
	$\chi 2(3)$	*p*-value	η_G^2	$\chi 2(1)$	*p*-value	η_G^2	$\chi 2(3)$	*p*-value	η_G^2
Pupil size	2.06	0.559	0.06	3.14	0.077	0.04	0.09	0.759	//
Saccade frequency (sacc/s)	6.49	0.090	0.36	2.75	0.097	< 0.01	0.97	0.809	//
Mean fixation duration (s)	1.07	0.783	0.14	0.20	0.656	0.05	3.01	0.390	//
Blink frequency (blink/s)	3.08	0.380	0.06	1.04	0.308	0.03	4.56	0.207	//

Note. η_G^2 could not be computed for the interaction model because of uneven number of reports in each block (rejected data during filtering).

On the other hand, the mechanism responsible for the increase in MW frequency under the automated condition should have prevailed over this possible effect of unfamiliarity. There are two constructs, which may be complementary, which may account for this interaction between time and level of automation over MW frequency. First, complacency might be generated by the high reliability of the system and lower monitoring performance. Complacency is an issue of monitoring automation generated by an uncritical reliance on the system (Parasuraman, Molloy, & Singh, 1993). Complacency has been linked to longer reaction time (Bahner, Hüper, & Manzey, 2008; Manzey, Bahner, & Hüper, 2006), loss of situation awareness (Endsley & Kiris, 1995) and failures of detection (Parasuraman et al., 1993). In our experiment, participants encountered no error during the first three blocks. Given that the system never committed any miss or error, participants may have thought that it would remain perfectly reliable. In this context, their perception of the required workload might evolve: since the automated system does not seem to require their attention to function properly, participants would redirect their cognitive resources towards more personal matters and mind wander more. The higher perceived workload under the manual condition supports our analysis. Moreover, this could explain why participants, who were novices in supervising the system, exhibited an increase in MW frequency only after some time, while pilots with thousands of hours flying time in the study by Casner and Schooler (2015) experienced MW immediately without temporal evolution. These evidences suggest a mediating influence of system familiarity in MW frequency temporal evolution. This position would introduce a third possibility within the overload/underload theory debate (Pattyn et al., 2008; Warm et al., 2008). Although the task complexity does not change, the operator's perception could evolve based on their perception of the system and the overall situation (e.g., trust, familiarity). As pointed out by Seli and colleagues (Seli et al., 2016; Seli, Carriere, & Smilek, 2015), there is strong evidence that people can exert some control over their MW. This is in accordance with Casner and Schooler's (2015) results, who demonstrated that cognitive resources freed by automation in peaceful situations are not allocated to task planning, but rather to MW. Moreover, our analysis is in line with studies that observed MW increase in a low-probability-signal environment (Berthié et al., 2015; Galera et al., 2012), with the time elapsed performing the task (McVay & Kane, 2009; Smallwood et al., 2003; Smallwood, Riby, Heim, & Davies, 2006) and the view of complacency as a multiple-task strategy (Bahner et al., 2008; Moray & Inagaki, 2000). Operators save cognitive resources allocated to the low-event automated task, in order to perform better on another task (MW), which is considered more interesting or useful, regardless of experiment instructions.

The second possible explanation is a disengagement from the task linked to a loss of agency. When dealing with automation, operators give up their direct control over the system for a monitoring role in the supervisory control loop (Moray, 1986; Sheridan, 1992). They may experience a loss of agency (i.e., the ability to feel in control; Wegner, 2002). Multiple studies pointed to a limit in the automation level beyond which users felt less in control (Berberian, Sarrazin, Le Blaye, & Haggard, 2012; Coyle, Moore, Kristensson, Fletcher, & Blackwell, 2012), leading to a form of disengagement from the task at hand (Haggard, 2017). Interestingly, Szalma (2014) described a similar disengagement when applying the Self-Determination Theory (Ryan & Deci, 2000) to human-system interactions. The inability of a system to support autonomous behavior may lower motivation and create an externalization of task goals (i.e., a process by which operators reject the value of a goal). In our experiment, given that participants did not validate, but rather only acknowledged the system's actions, they initially experienced a loss of agency, causing a decrease in their motivation, leading to a faint sense of responsibility. This process chain could lead participants to reallocate cognitive resources from the task to MW, unconsciously trying to optimize time and mental resources from their perspective. Further studies are needed to distinguish the respective impacts of agency decrease and complacency on MW emergence.

4.2. Influence of MW over oculometry

Our second result concerns oculometric measures. Given that we only took intervals without actions, pupil diameter signals were only influenced by tonic pupil activity (i.e., the sustained component of the pupillary response, expressed as an absolute pupil diameter, as opposed to phasic activity reflecting changes linked to events). We highlighted a lower pupil diameter during MW, as did several studies on MW (Faber, Bixler, & D'Mello, 2017; Grandchamp et al., 2014; Mittner et al., 2014). Moreover, the literature on vigilance already showed a link between a smaller pupil and periods of lower sensibility to external stimuli (McIntire et al., 2014; Nishiyama, Tanida, Kusumi, & Hirata, 2007). Taken together, these results are in line with the view of MW as a phenomenon inducing a decoupling from the environment. However, other research linked large pupils to slow and inaccurate responses (Gilzenrat, Nieuwenhuis, Jepma, & Cohen, 2010; Smallwood et al., 2011), or more directly to MW during a word-by-word reading task (Franklin et al., 2013). Addressing this debate, two recent studies by Unsworth and Robison (2016) and Konishi, Brown, Battaglini, and Smallwood (2017) demonstrated an inverse U-curve relationship between pupil diameter and performance. They demonstrated that a smaller pupil diameter was linked to drops in performance and MW episodes associated with internally directed cognition. In contrast, a larger pupil diameter was correlated with external distractions (e.g., conversation, noise, itching) and was also accompanied by a decrease in performance. These results corroborate our study and stress the need to investigate these attentional states.

In contrast to pupillometry, other oculometric measures did not exhibit significant sensitivity to MW. This could be due to the relatively low number of participants ($N = 17$), which yielded statistical power levels of 0.82, 0.53 and 0.49 for saccade frequency, blink frequency and fixation duration models, respectively (all calculated with standard values of $\alpha = 0.05$ for two-tailed tests). However, one should be careful with an *a posteriori* power analysis using output data, as pointed out by Hoenig & Heisey (2001). Nevertheless, many notable studies have used a number of participants within our range (Smilek et al. (2010), 12 subjects; Uzzaman and Joordens (2011), 22 subjects; He et al. (2011), 18 participants; Franklin et al. (2013), 13 participants; Braem, Coenen, Bombeke, van Bochove, and Notebaert (2015), 20 participants). They used reading tasks (with the notable exception of Grandchamp et al., 2014), which make extensive use of eye movement. Our task does not require constant saccades between words, since obstacles only appear at a slow rate. Our result could point to important task mediators of MW influence over oculometric markers, such as event rate or cognitive demands. However, we need more studies to make sure that these results are not due to a lack of participants.

4.3. Stability of pupillometry

Finally, the last result is the stability of pupillometric markers with respect to automation and time. Cheyne, Solman, Carriere, and Smilek (2009) recently proposed the integration of intensity of environment decoupling as a characteristic of MW episodes. They used a Sustained Attention to Response Task (SART, a form of GO/NOGO task; Robertson, Manly, Andrade, Baddeley, & Yiend, 1997) to match errors and reaction time evolution with each level of their model. If this model were true, there is little doubt that physiological markers would show some sensibility to MW intensity. However, no influence over oculometric markers was observed. Several explanations can be proposed. First, our protocol, which differs from previous protocols, may not be able to reveal such a tendency (this could be due to the relatively low number of participants, $N = 17$). Second, intensity may not regulate MW impact over pupillometry. Third, there may not be any intensity in MW episodes, each inducing the same environment decoupling. Indeed, the study by Cheyne et al. (2009) falls under the concerns expressed by Head and Helton (2016). Further neural studies are necessary to answer this question.

In the near future, the massive use of automation in everyday systems will reinforce the OOTL phenomenon. Our results show that automation increases MW frequency after a certain time. The MW literature in ecological tasks already revealed how the phenomenon increases risks in critical environments. Such results stress the necessity to study in more detail the relationship between MW and the OOTL performance problem. Possible improvements include the study of reliability and complacency by manipulating the number of conflicts and automation errors. Another possibility is to highlight the impact of the operator's engagement in the task. Finally, perceived workload is not to be overlooked. The use of electroencephalograms would allow continuous measurement to precisely assess its impact on MW frequency. However, such a protocol requires the influence of perceived workload and MW over neural measures to be discriminated. Eventually, the expected outcome is the design of automated systems with the ability to adapt their behavior to operators' MW episodes. We hope that such a system may enhance safety in critical automated environments.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.concog.2018.09.012.

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