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Encoding decisions and expertise in the operator's eyes: Using eye-tracking as input for system adaptation

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ABSTRACT

Keywords:

Eye-tracking
Human factors
Decision-making
Air Traffic Control
Adaptive system
Machine learning
Case-Based Reasoning

We investigated the possibility of developing a decision support system (DSS) that integrates eye-fixation measurements to better adapt its suggestions. Indeed, eye fixation give insight into human decision-making: Individuals tend to pay more attention to key information in line with their upcoming selection. Thus, eye-fixation measures can help the DSS to better capture the context that determines user decisions. Twenty-two participants performed a simplified Air Traffic Control (ATC) simulation in which they had to decide to accept or to modify route suggestions according to specific parameter values displayed on the screen. Decisions and fixation times on each parameter were recorded. The user fixation times were used by an algorithm to estimate the utility of each parameter for its decision. Immediately after this training phase, the algorithm generated new route suggestions under two conditions: 1) Taking into account the participant's decisions, 2) Taking into account the participant's decisions plus their visual behavior using the measurements of dwell times on displayed parameters. Results showed that system suggestions were more accurate than the base system when taking into account the participant's decisions, and even more accurate using their dwell times. Capturing the crucial information for the decision using the eye tracker accelerated the DSS learning phase, and thus helped to further enhance the accuracy of consecutive suggestions. Moreover, exploratory eye-tracking analysis reflected two different stages of the decision-making process, with longer dwell times on relevant parameters (i.e. involved in a rule) during the entire decision time course, and frequency of fixations on these relevant parameters that increased, especially during the last fixations prior to the decision. Consequently, future DSS integrating eye-tracking data should pay specific care to the final fixations prior to the decision. In general, our results emphasize the potential interest of eye-tracking to enhance and accelerate system adaptation to user preference, knowledge, and expertise.

1. Introduction

In dynamic environments, human operators must constantly monitor and integrate incoming information in order to optimize their decision-making. This is particularly true in Air Traffic Control (ATC) ground operations, which require fast, safe, and efficient management of aircraft and vehicles on taxiways and runways. Indeed, today's increase of aircraft traffic (Eurocontrol, 2016) challenges not only airport infrastructure but also the operators' cognitive capacities. Therefore, developing automated tools to assist Air Traffic Controllers (ATCo) in the ground flow management seems to be the best solution. However, current Decision Support Systems (DSS), i.e. tools that support decision-

making in complex activities, do not fully take into account the dynamic nature of airport ground management. In addition, previous research has considered separately airports and ATCo, without integrating the interplay of both (Atkin et al., 2010; Jiang et al., 2015). Routing operations often require real-time adaptation from the system, and therefore the integration of human expertise, preference, decisions, and knowledge is an important factor for the development and robustness of a system. Moreover, the collection of the user's actions would be more complete with the awareness of what features of the interface are visually inspected and what strategies the user exhibits (Bednarik, 2005).

The ability of a system to learn from experience improves its

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knowledge base and avoids repeating the same mistakes. In the ATC domain, [Bonzano et al. \(1996\)](#) and [Liang \(2015\)](#) showed that a Case-Based Reasoning (CBR) approach can be used in DSS during conflict resolution tasks. The principle of CBR is to solve a new situation by reusing the solution of the most similar previous case. However, the evaluation of the distance between the new situation and the previous one is complex and difficult to objectify. Actually, the number of features (or parameters) that differentiate two situations can be huge and highly context sensitive. Features that are relevant in a given situation may not be equally significant in another one. For example, during ATC ground operations, the importance of parameters such as aircraft type/size can be more critical for the decision (to determine the best route) when visibility is poor. The analysis of the eye fixation of the operator on the interface may give reliable indications regarding the user's decision-making process and would allow specifying weights for each parameter in a machine learning model, according to its "presumed" criticality in the decision.

1.1. Eye movements as a window into attentional processing and decision-making

Past studies in experimental psychology ([Deubel and Schneider, 1996](#); [Hoffman and Subramaniam, 1995](#); [Kowler et al., 1995](#)) and neuropsychology ([Kustov and Lee Robinson, 1996](#); [Mohler and Wurtz, 1976](#)) established the close link between eye movements and attentional processes. [Carrasco \(2011\)](#) describes visual attention as a selective process that enables us to prioritize and process relevant visual information in a current task. This tendency to gaze towards a particular area according to the current goal was demonstrated a long time ago in the seminal study of [Yarbus \(1967\)](#). In his experiment, Yarbus demonstrated that the trajectories followed by the gaze on a scene (e.g. a painting) are strongly dependent on the instructions given to the participants (e.g. remember the people's clothes on the painting). Many past studies also indicated that the decision maker tends to gaze more at attributes with greater importance ([Glöckner and Herbold, 2011](#); [Wedell and Senter, 1997](#)). This trend to overwhelmingly attend to important or high utility information is called the "utility effect" and has been demonstrated across a variety of tasks (for a review, see [Orquin and Looze, 2013](#)). For example, in a risky choice task, participants were asked to make quick decisions between two gamble sets with different expected values. They showed that attention to a gamble outcome increased when its expected value is higher, resulting in a more comprehensive information search (amount of fixations) and deeper processing (mean length of a single fixation).

Gaze behavior is also modulated by preferences and by the stage of the decision process, as showed by another study using a forced-choice decision task ([Glaholt and Reingold, 2009](#)). Participants were asked to select a preferred image, or the most modern image. The authors demonstrated robust biases in both gaze duration and gaze frequency towards the chosen items, regardless of the nature of the decision. Interestingly, dwell duration and dwell frequency reflected different stages of the decision process, with a first "screening" stage characterized by selective processing, in which relevant stimuli are encoded in greater depth (longer dwell times) and irrelevant stimuli are less encoded (shorter dwell times) or excluded from further processing; and a later "evaluative stage" of processing that involves the comparison of alternatives and results in a higher frequency of dwells on the chosen item. In this interpretation, the dwell duration bias is related to the encoding of decision alternatives whereas the dwell frequency bias may reflect another process (possibly post-encoding) such as the evaluation and comparison of relevant alternatives. This dissociation of the visual processing in terms of two-stage models, or in two routes of visual processing in the brain, can be found in numerous publications. [Trevathan \(1968\)](#) coined the terms "ambient" and "focal" as labels for distinct brain mechanisms that serve parallel functions of spatial orientation (the subcortical pathway) and visual identification (the

cortical pathway). Different patterns of eye movements were attributed to the focal-ambient modes of information acquisition ([Unema et al., 2005](#); [Velichkovsky et al., 2005](#)), that has been variably referred to as evaluating-orienting ([Ingle, 1967](#)), examining-noticing ([Weiskrantz, 1972](#)), skimming and scrutinizing ([Lohmeyer and Meboldt, 2015](#)), or exploring and exploiting ([Dehais et al., 2017](#); [Dehais et al., 2015](#)). In the last example, a fixation/saccade ratio expresses the balance between different visual strategies: visual search and visual processing ([Goldberg and Kotval, 1999](#)).

1.2. Using eye movements to improve system adaptation

Taking this link between attention and eye movement into account, a wide variety of applications have emerged ([Duchowski, 2002](#)). [Giannopoulos et al. \(2016\)](#) used eye-tracking in order to provide guidance to the user facing pervasive environments with high density of visual information. Their experiment took place in a virtual retail, and guidance was contingent upon gaze position. For example, when the user's gaze was directed towards a product on a shelf (e.g. cereal products), an advertisement video of this product was shown on a monitor located in the vicinity. Furthermore, when a gaze fixation on the monitor occurred, an attention-getter (flashing) at the position of the advertised product was triggered in order to redirect the attention back to the product. This idea of using an eye tracker to provide real-time guidance and to reduce attentional effort is also explored in a study of [Kajan et al. \(2016\)](#). They developed an eye-tracking based technology that extracts information that is most likely relevant to the user. These extracted pieces of information are presented to the user and sorted according to their estimated importance, in the so called "PeepList". As the user interacts with the display, for each item on the screen, a vector of gaze metrics (gaze time, fixation count, visit counts, and fixated last) is computed. Results showed that eye-tracking was a valuable real-time implicit source of information about what the user was searching and the PeepList principle considerably improved the efficiency of obtaining required information. In the learning context, [Hutt et al. \(2016\)](#) used different gaze metrics to detect the occurrence of mind wandering, an unintentional shift of attention from task-related to task-unrelated thoughts, which can be deleterious to the learning process. Participants self-reported mind wandering episodes by responding to thought-probes ("yes" or "no" based on whether they were mind wandering at the time of the probe). Their eye movements were monitored and a supervised machine learning technique was then used to try to discriminate between positive and negative responses to the probes. By studying several eye movement metrics (fixation duration, saccade duration, fixation to saccade ratio etc.), they were able to automatically classify mind wandering events, which may help to re-engage learners and thus improve learning.

In the automobile domain, [Doshi and Trivedi \(2009\)](#) explored the possibility of developing an intelligent driver assistance system capable of predicting drivers' intent to change lanes. They used a combination of eye gaze position (among nine possible locations) and head motions to feed a discriminative classifier. Head motions, together with lane and vehicle data, served as a very good indicator of lane-change intent. However, eye gaze was less informative than head motions in their study. According to the authors, the driver has a premeditated gaze target when planning to change lanes, and thus prepares the gaze shift with a preliminary head movement. Thus, the intention of the driver is captured earlier with head monitoring than waiting for the subsequent eye-gaze shift. However, such results certainly do not apply to systems displayed on a classical computer screen, as they do not require large head movements. In the same domain, [Fletcher and Zelinsky \(2009\)](#) used eye movements for the online detection of inattention in drivers. They showed that correlating eye gaze with the road scene allowed to detect missed road events and to warn the driver, providing them the time to react before an impending accident. More recently, [Tremblay et al. \(2018\)](#) proposed to explore the possibility of using eye-

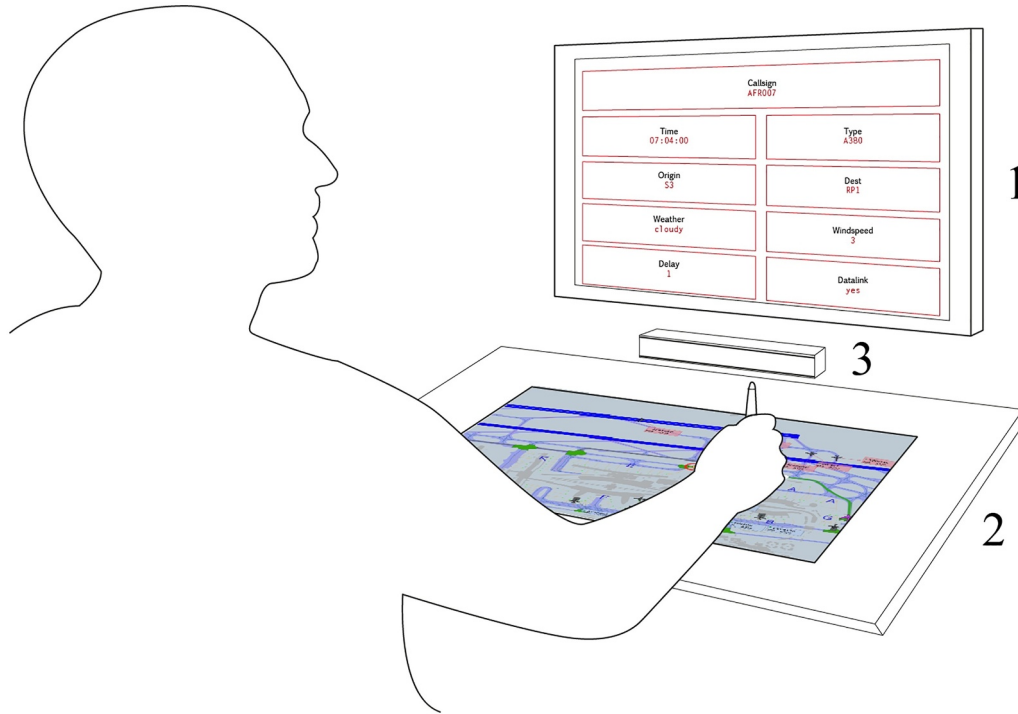


Fig. 1. Experimental set-up. 1) The upper screen with all parameters. 2) The lower touch screen with the interactive ATC interface. 3) The eye-tracking system, located below the upper screen.

tracking to optimize the visual circuits of surveillance operators who must monitor a large number of screens. One objective is to provide alerts when ocular behavior is considered sub-optimal (e.g. too much focused on a single screen), in order to avoid attentional tunneling or inattention blindness. Importantly, several studies showed that it is possible to use eye movement to better understand the operator's decision-making (Morrison et al., 1997; Wilson et al., 2012) and upcoming choices (Peysakhovich et al., 2015), which would allow providing personal information to users (Majaranta and Bulling, 2014) and to capture their preferences and/or expertise.

1.3. Objectives and hypotheses

DSS with learning capabilities are developed since several years (e.g. Gultepe et al., 2014; Piramuthu et al., 1993) but to the authors' knowledge, very few integrate objective measures of the operator such as eye movements. Some studies on DSS employed eye-tracking, but this was done to evaluate the display (Morrison et al., 1997), or to examine how the information presentation facilitates or affects decision-making (Kuo et al., 2009). These studies did not attempt to improve suggestions from the DSS on the basis of the eye movements, which is the core of the current paper. The recording of the visual scans can contribute not only to an evaluation of the design of a DSS but also to our understanding of how information was acquired and used for decision-making tasks. Enabling the understanding of the ATCo's decision with eye-tracking can be useful to improve the adaptation of a system to user preferences, knowledge, or expertise. Indeed, when the number of parameters that differentiate two situations is high, the learning phase of the CBR system can be long and sub-optimal if it is only based on the previous user choices and the indistinctive analysis of all parameter values (high combinatorial possibilities).

In this paper, we describe the technical development and the testing of a DSS, integrating objective measurements from the user. We computed a route suggestion algorithm that can integrate both previous route choices from the ATCo's and the total dwell times on each parameter. The measure of the time spent gazing at the parameters enabled

to specify higher weights to the parameters that were likely important for the decision. The objective of this study was twofold. First, we explored the performance of our DSS according to several levels of automatic adaptation during an ATC ground taxiing operation simulation. Second, we explored more deeply the dynamics of visual attention during decision-making. We hypothesized that 1) the use of the previous decisions will allow an improvement of the performance of the adaptive route suggestion, and that 2) parameters that are relevant for the decision will be gazed for a longer period of time, and therefore specifying higher weights to parameters subjected to longer fixation will help to further enhance the performance of the adaptive route suggestion. Finally, 3) we hypothesized that fixations on relevant parameters should be longer and/or more frequent, more specifically in the last moments of the decision-making process.

2. Materials and methods

2.1. Participants

Twenty-two healthy volunteers (7 women and 15 men, mean age = 25.0 years, SD = 4.56) were recruited for this study. All were French undergraduate students or researchers familiar with the aeronautical domain. None of them had a history of neurological disease, psychiatric disturbance, substance abuse, or taking psychoactive medications. All participants gave written informed consent in accordance with the local ethical board committee. The study complied with the Declaration of Helsinki for human experimentation.

2.2. Procedure

Participants were seated in front of two screens placed on top of each other with their respective interfaces, see Fig. 1. Several parameters with associated values were displayed on the upper screen. The lower touchscreen provided an interactive interface (developed during the Modern Taxiing project, MoTa) representing the south part of Roissy-Charles-de-Gaulle airport (Paris, France) and showed DSS

routing suggestions. On this latter interface, route suggestions can be either accepted or modified, by adding a waypoint or changing the destination using a stylus.

2.3. ATC task

Participants performed a task simulating airport taxiing operations. We designed an ATC-like synthetic environment that provides an optimal balance between ecological validity and experimental control. Such microworld simulates key features of dynamic systems within a controlled setting. The generic design and the underlying tasks make it applicable beyond the ATC domain to a range of surveillance/monitoring activity (Imbert et al., 2014). Another advantage of using synthetic microworld is that it allows recruiting participants that are not necessarily qualified professionals. Several studies employing synthetic ATC simulations involved novices in the ATC domain or students with some ATC knowledge (Hou et al., 2017; Salden et al., 2006). For example, in the current experiment, a fully realistic simulation would have required numerous qualified controllers with a specific training for the Roissy-Charles-de-Gaulle airport.

Concretely, at the beginning of each trial, the call sign of a new aircraft was presented on the upper screen. The participant selected the corresponding aircraft in the lower screen with the stylus (the call sign of each aircraft was displayed on its radar label). Once selected, a set of parameters with associated values, including time, type, origin, destination, weather, wind speed, delay, and datalink availability, were displayed on the upper screen, below the call sign; and a route suggestion was simultaneously displayed (a grey line) on the lower screen, see Fig. 2. The participant had to accept or modify the suggested trajectory, basing the decision on the parameter values displayed on the upper screen.

All possible values of the parameters are synthesized in Table 1. After having visualized the parameters and the suggested route, the participant had to accept or modify it according to a set of rules.

Participants had to apply four basic rules during the experiment (Table 2). Each of the four rules was defined by a combination of two (R2 and R4) or three (R1 and R3) parameter values, associated to an aircraft route constraint. A rule was applicable during a given trial when all of the parameter values (context) were present. The objective of the participants was to identify if a rule was applicable, and in that case, to ensure that the trajectory of the aircraft respected the route constraint. For example, if “Middle2” and “A380” values were

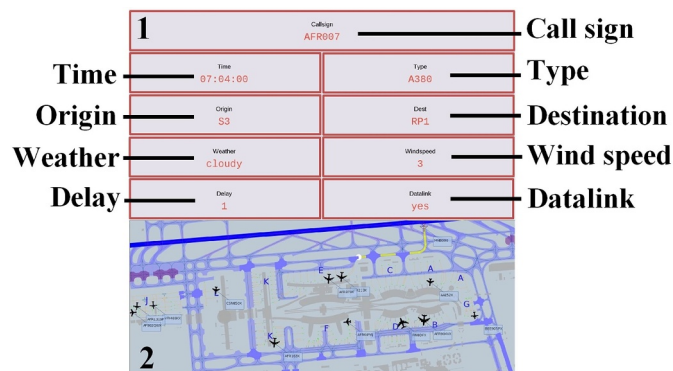


Fig. 2. Focus on the two interfaces used for the airport routing task: 1) Upper screen displaying the call sign of the aircraft currently under control and its 8 associated parameter values (time, type etc.). Each red rectangle (except the call sign) represents an area of interest used in the eye-tracking analysis to estimate the time spent gazing at each parameter; 2) lower screen displaying the airport and the DSS route suggestions (the path was displayed in grey, and then it turned to yellow, as shown in the illustration, when participants modified it). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1

All possible parameter values of the simulation.

Type	A319, A320, A321, A330, A380, B767, B772, E190
Origin	G, RP2, RP5, GE9, P3, J, S1, S2, S3, MIDDLE2
Destination	RP1, RP3, KL4, GE3, RP6, UC4, P2, 26R, 27L
Datalink	yes, no
Delay (min)	0, 1, 5, 10
Weather	sunny, cloudy, snowy
Time	07:00, 12:00, 15:00, 18:00
Wind speed	0, 8, 16, 22

Table 2

The four rules given to the participants, indicating the relevant context and the associated route constraints.

Rules	Context	Route constraint	Known by the DSS
R1	Weather = snowy Time = 07:00 Dest = 26R	Go through taxiway W9 (Z1)	No
R2	Origin = Middle2 Type = A380	Avoid taxiway E (Z2)	Yes
R3	Delay = 10 Datalink = yes Dest = 26R	Go through taxiway RP (Z3)	No
R4	Datalink = yes Dest = RP3	Go through taxiway R (Z4)	Yes

displayed for the parameters “Origin” and “Type”, respectively, rule R2 had to be applied. In this case, the participant had to ensure that the aircraft did not use taxiway E (see Table 2, Rule R2), otherwise the participant had to reject the DSS trajectory suggestion and modify the path of the aircraft (in order to avoid taxiway E) by adding waypoints or by changing the route with the stylus, before the validation. If the route suggestion respected the route constraint of the applicable rule, or if no rules were applicable, the participant simply had to validate the route suggestion. A printed document with all four rules was made available to the participants during the entire experiment.

Fig. 3 shows the lower screen with the four taxiways that were involved in the four rules. According to the route constraint of a given rule, the indicated taxiway should be followed (Z1, Z3, or Z4) or avoided (Z2) by the aircraft under control during the current trial. The order of rules varied across participants to avoid an order effect. In each trial, zero or one rule was applicable. Two rules were known by the route suggestion algorithm (R2, R4) and two others were unknown (R1, R3). Consequently, the system always provided a correct suggestion for R2 and R4 and had to learn the two other rules. The information concerning the fact whether the rule was known or unknown by the system was not provided to the participants.

2.4. Eye-tracking measurements

During the experiment, eye fixations on the upper screen were recorded with a remote SMI RED eye tracker (SensoMotoric Instruments GmbH, Germany) at a 60 Hz sampling rate. For all eye movement analyses, the detection threshold that defined a fixation was set to 80 ms (Causse et al., 2016; Quéward et al., 2016; Salvucci and Goldberg, 2000). Eight areas of interest (AOIs) were defined, one for each parameter (red rectangles around the parameters in Fig. 2, call sign was not included in the analysis as this parameter was never involved in a rule). For each trial, the total dwell times on each of the eight AOIs was recorded, and these values were used by the routing suggestion algorithm in order to weight the parameter, i.e. a longer total dwell time on an AOI will result in a higher weight for the corresponding parameter. It is important to note that the algorithm was never aware about the relevance (i.e. involved in a rule or not in the current trial) of the different AOIs. The algorithm determined the importance (weight) of each AOI

only on the basis of the total dwell time spent on it by the participant. Also, in order to provide a deeper understanding of the dynamics of the ocular behavior during the decision-making process, we examined other metrics such as the mean dwell times/dwell frequencies on the relevant and irrelevant parameters for the entire trial duration and then during the first dwells (all dwells occurring before a given AOI was revisited for the first time in the current trial, so a maximum of eight first dwells could occur during each trial) and the revisit dwells (all dwells starting from the first time an AOI was revisited). We also investigated the temporal evolution of these metrics in a more detailed manner, i.e. during the first three dwells and the last three dwells before the decision. These exploratory metrics were not used by the algorithm.

In order to familiarize themselves with the task, each participant performed a training phase on 32 unique trials, after which they performed the experiment.

- A learning phase with the participant performing the ATC task. Each participant completed 54 trials (presented randomly), split 30/24: 30 trials where no rules were applicable and 24 trials in which a rule (R1, R2, R3, R4) was applicable (six trials for each of the four rules);
- A testing phase (automated), in which the algorithm computed twice new route suggestions for new 42 trials, split 14/28 (seven trials for each of the four rules). This phase took place once the participant finished the learning phase, thus the testing phase never included data from other participants.

- Using previous decisions of the learning phase;
- Using previous decisions plus parameters weights of the learning phase (the weights were calculated based on the total dwell times spent on each AOI by the participant during the learning phase).

lower screen (which triggered the display of the various parameter values on the upper screen). Each trial (and thus the recording of the dwell times) ended when a route was validated (modified or not).

The route suggestion algorithm relied on three main components illustrated Fig. 5: (A) a classifier using k -nearest neighbor, (B1) a graph-based route suggestion, and (B2) an historic-based suggestion. The graph-based algorithm updated its edge weights for each new context using fixed rules. The classifier used the previous route validations to classify, for a given context, if the suggestion given by component (B1) would be accepted or refused. This classification was done using a k -nearest neighbor (knn), which selects the k feature vectors that have a minimal distance regarding the distance metric. The k -value of the knn was fixed as $k = 3$. This value was a good compromise, a k -value too small can lead to noisy decision boundaries, and a k -value too large can lead to over-smoothed boundaries.

$$C = \begin{bmatrix} c_1: \text{type [e.g., A319, A320, etc.]} \\ c_2: \text{origin [e.g., G, RP2, RP5, etc.]} \\ c_3: \text{destination [e.g., RP1, RP3, etc.]} \\ c_4: \text{datalink [yes | no]} \\ c_5: \text{delay [0, 1, 5]} \\ c_6: \text{weather [e.g., sunny, cloudy, etc.]} \\ c_7: \text{time [e.g., 07:00, etc.]} \\ c_8: \text{windspeed [e.g., 0, 8, etc.]} \end{bmatrix} \quad (1)$$
$$W = \begin{cases} [d_{type} \ d_{origin} \ d_{destination} \ d_{datalink} \ d_{delay} \ d_{weather} \ d_{time} \ d_{windspeed}]^T, & \text{if using gaze data} \\ [1 \ 1 \ 1 \ 1 \ 1 \ 1 \ 1 \ 1]^T, & \text{otherwise} \end{cases} \quad (2)$$
$$\|W\| = \sqrt{\sum_{i=1}^n w_i^2}$$

Each graph-based route suggestion was labeled as accepted when the route suggestion ($R_{\text{suggested}}$) was similar to the validated route

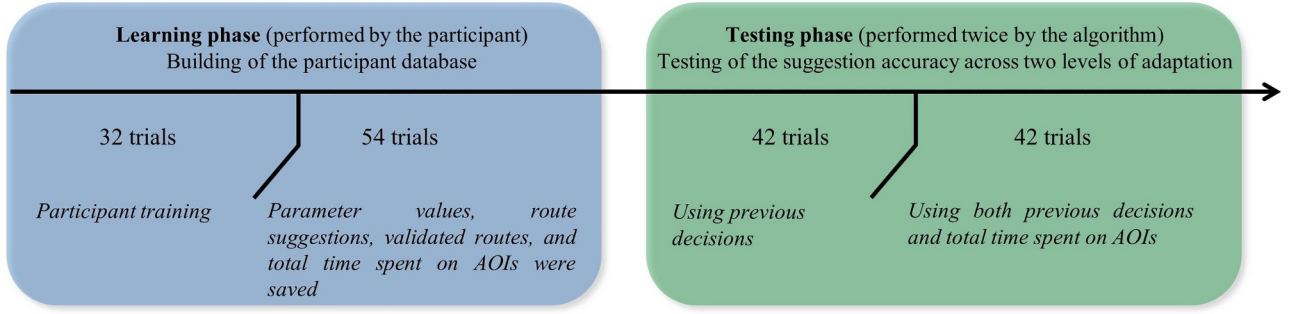


Fig. 4. Timeline of the experiment (the 32 training trials were not used by the algorithm during the testing phase).

($R_{\text{validated}}$) or refused otherwise:

$$y = \begin{cases} 1, & \text{graph-based suggestion accepted} \\ 0, & \text{graph-based suggestion modified} \end{cases} \quad (3)$$

One validated route suggestion is represented by:

$$T = \begin{cases} C \\ \hat{W} \\ y \\ R_{\text{suggested}} \\ R_{\text{validated}} \end{cases} \quad (4)$$

The distance between a new context C and one previous validated route suggestion T (trial) was computed by summing the product of the difference between each feature of the two contexts and its corresponding weight from the weight vector Eq. (5) and ((6)):

$$\langle C, T \rangle = \sum_{i=1}^n \hat{W}_i \delta(c_i, c_{Ti}) \quad (5)$$

$$\delta(a, b) = \begin{cases} 1, & a \neq b \\ 0, & a = b \end{cases} \quad (6)$$

For each new context, component (A) predicted if the graph-based shortest path would be accepted or refused using the knn algorithm. If (A) predicted that the graph-based route suggestion will be accepted, then this route was used. If (A) predicted that the graph-based route suggestion will be refused, then the validated route from the previous decisions with the shortest distance context from the current context (based on the similarity of the eight parameter values) was used (noted as R_{historic}). As this route was not necessarily going through the actual vehicle position, a new route was computed by finding the shortest path between the current vehicle position and one point of the R_{historic} route. Instances were chosen to ensure that using only previous decisions

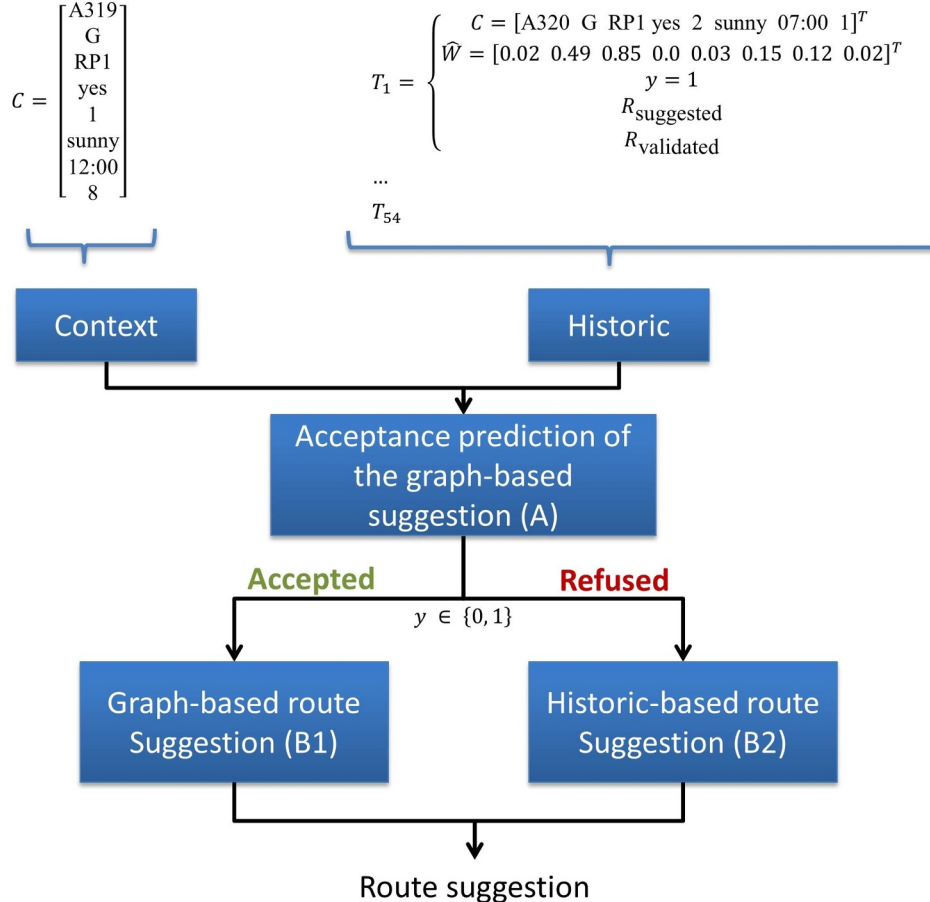


Fig. 5. Route suggestion process. The classifier (A) uses the current context and the historic of the previous routes validated by the participant to predict if the graph-based route suggestion (B1) will be accepted or refused. If acceptance was predicted, the graph-based route suggestion (B1) was displayed to the user, and in the other case, the historic-based route suggestion (B2) was displayed.

would not allow the algorithm to reach 100% accuracy. Indeed, several trials shared several common parameter values but they did belong to different rules (e.g., several trials are highly similar and shared six parameter values but they still correspond to different rules, whereas other trials shared few common parameter values but correspond to the same rule). Thus, the maximal performance of the algorithm using only previous decisions (in case the participants accepted or modified all the suggestions appropriately) was 85.71% (36 out of 42 trials), as different rules had to be followed in these very similar instances.

3. Results

The results of this study were divided in two parts: First, we analyzed the performance of the routing suggestion algorithm according to the three levels of adaptation: 1) No adaptation (the same route suggestions as during the learning phase), 2) using previous decisions of the learning phase, and 3) using previous decisions plus the total dwell times on each AOI of the learning phase. As previously mentioned, the algorithm was not given the input regarding the relevance of the parameters, and this information was never used during the training phase. For each of the 24 trials, we predetermined (during the experimental design) whether a rule was applicable or not (i.e. according to the parameter values). In case it was applicable, the parameters involved in this rule were labeled as relevant, whereas the others were considered as irrelevant for the decision. This information was available to us for post-hoc analysis purposes only (comparison of the weight values for relevant vs. irrelevant parameters and all exploratory eye-tracking analyses). Second, we conducted exploratory eye-tracking analysis to better understand the behavior underlying the decision process, in particular, the mean dwell times on the relevant and irrelevant parameters, and the probability to dwell on a relevant parameter according to specific periods of the decision-making process. Two participants were excluded from the analysis, one due to incorrect recording of the data and the other for eye-tracking signal loss during the acquisition.

3.1. Performance of the route suggestion algorithm

Fig. 6 presents the results of the testing phase: The mean percentage of correct suggestions for each level of adaptation. ANOVA showed a significant effect of the level of adaptation ($F(1, 19) = 191.76$, $p < 0.001$, $\eta^2_p = 0.90$) and Tukey's post-hoc test revealed that accuracy increased across each of these levels ($p < 0.001$). As previously mentioned, the route suggestion algorithm was not informed on R1 and R3, and consequently all trials in which R1 or R3 were applicable required a modification from the user. Thus the route suggestion accuracy without adaptation was necessarily 66.67%, corresponding to 28 trials out of 42 with correct suggestions, 14 correct suggestions because the algorithm knew two rules ($R2 + R4 = 14$ trials) plus 12 trials where no rule was applicable (thus any trajectory was correct). Using previous validation decisions, the route suggestions were accurate at an average of 82.62% ($SD = 4.37\%$) and the performance again improved when the total dwell times on each AOI was used to weigh the distance function, with an average of 89.17% of correct suggestions ($SD = 6.06\%$). Weights were significantly impacted by the relevance ($t(19) = 16.82$, $p < 0.001$): The use of total dwell times spent on parameters in our algorithm resulted in higher mean weights for relevant ($M = 0.43$, $SD = 0.05$) vs. irrelevant parameters ($M = 0.18$, $SD = 0.03$). This result indicates that participants gazed more in the direction of the relevant parameters (because weights are directly computed on the basis of this eye metric).

3.2. Exploratory eye-tracking analysis

All following exploratory eye-tracking analyses were performed only on the 24 trials of the learning phase in which a rule was

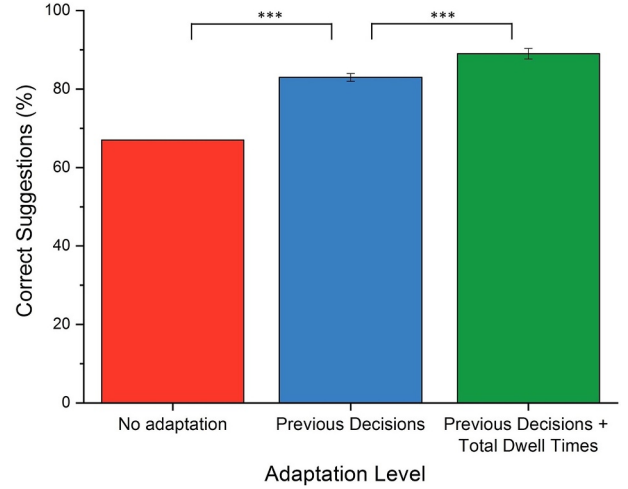


Fig. 6. Percentage of correct route suggestions reached by the algorithm as a function of the level of adaptation. The existing data variability in the previous decisions and previous decisions plus total dwell times condition was due to variations in the route modification (e.g. participants could erroneously validate route suggestions that did not respect the rule constraints) and in the individual eye fixation patterns over the interface. Error bars represent the standard error of the mean, triple Asterisks indicates $p < 0.001$.

applicable. We present how visual behavior evolved according to the relevance of the parameters (known only to the experimenter, never used by the algorithm) in each trial.

3.2.1. Total fixation time on parameters according to their relevance for the decision

We examined how fixations were distributed between the relevant and irrelevant parameters (total dwell time on each type). Logically, and as suggested by the higher mean weights for relevant parameters, the total dwell times spent by participants on relevant parameters was significantly higher than the one spent on the irrelevant parameters ($M = 514.30$ ms, $SD = 122.83$ ms; $M = 242.21$ ms, $SD = 85.16$ ms, respectively) ($t(19) = 13.01$, $p < 0.001$), as presented in Fig. 7. Triple Asterisks indicates $p < 0.001$.

3.2.2. Temporal dynamics of the fixations during decision-making

In order to examine how participants' visual attention evolved

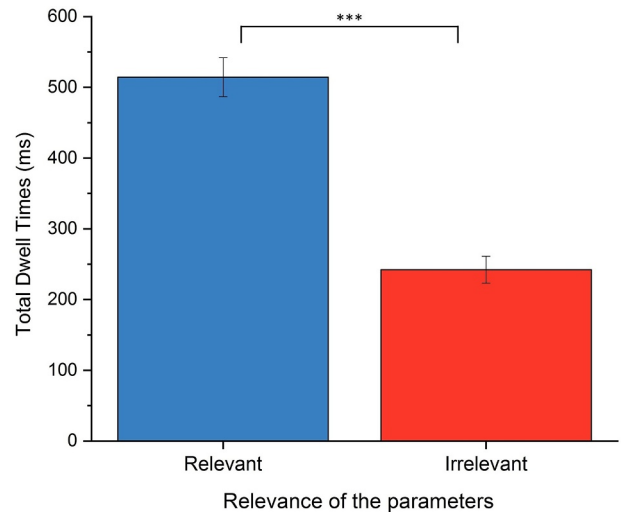


Fig. 7. Total dwell times (i.e. the average sum of all dwell times) on relevant and irrelevant parameters during the decision-making process. Error bars represent the standard error of the mean, triple Asterisks indicates $p < 0.001$.

during the decision time course, we explored the mean dwell times on the relevant and irrelevant parameters and the frequency of the dwells on relevant parameters during the first dwells and the revisit dwells, and in a more detailed manner during the first three dwells and the last three dwells before choice (note that a dwell can be categorized in several serial positions in the few trials in which less than six fixations were performed. For example, when only three fixations were observed, the three dwells were labeled as first/-3, 2/-2, and 3/last, respectively).

3.2.3. Mean fixation time for first versus revisit dwells according to the parameter relevance

We conducted a 2×2 ANOVA crossing the relevance (whether the dwell was in a relevant or an irrelevant parameter) and the position of dwells (first dwells = dwells prior to the first refixation on a given parameter, and revisit dwells = all others). We found higher mean dwell times for the relevant ($M = 330.35$ ms, $SD = 80.43$ ms) vs. irrelevant parameters ($M = 280.42$ ms, $SD = 49.60$ ms) ($F(1, 19) = 39.52$, $p < 0.001$, $\eta_p^2 = 0.68$; Tukey's HSD post hoc test, $p < 0.001$ in both comparisons). However, no main effect of the dwell position ($F(1, 19) = 1.25$, $p = 0.28$) neither Relevance \times Position interaction ($F(1, 19) = 1.34$, $p = 0.26$) was found on mean dwell times, see Fig. 8. These results showed that there was a bias in dwell duration towards relevant parameters all throughout the decision-making process.

3.2.4. Probability to gaze at a relevant parameter in first versus revisit dwells

The probability to dwell relevant items was higher during the revisits ($M = 0.57$, $SD = 0.09$) compared to the first dwells ($M = 0.40$, $SD = 0.07$) ($t(19) = 8.10$, $p < 0.001$), as shown in Fig. 9. Taken together, the two latter results suggest the existence of two biases: A bias in dwell duration occurring during the entire decision making process and a bias in dwell frequency mainly occurring in revisit dwells.

3.2.5. Mean dwell times and dwell frequency in the early and late moments of the decision

We conducted a 2×6 ANOVA crossing the relevance (relevant or irrelevant) and the position of dwells (the first three or last three dwells) for the dwell times. As expected, higher mean dwell times were found for relevant ($M = 335.25$ ms, $SD = 90.97$ ms) vs. irrelevant parameters ($M = 253.75$ ms, $SD = 72.26$ ms) ($F(1, 19) = 48.44$, $p < 0.001$, $\eta_p^2 = 0.72$). There was also a significant

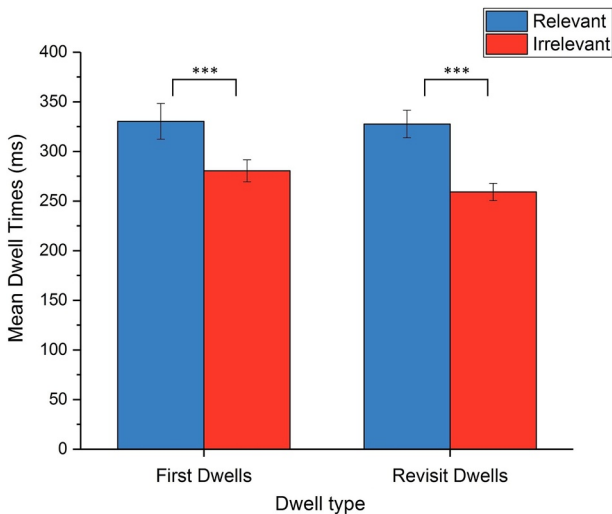


Fig. 8. Mean dwell times (i.e. average dwell time of each unique consultation) on relevant and irrelevant parameters for the first dwells and the revisit dwells. Error bars represent the standard error of the mean, triple Asterisks indicates $p < 0.001$.

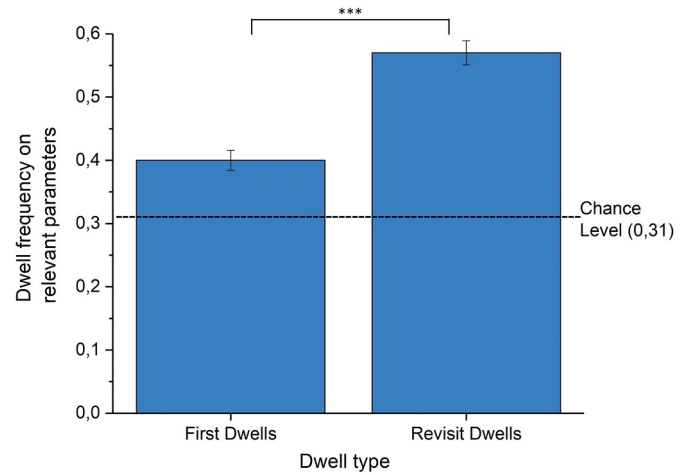


Fig. 9. Probability to dwell a relevant parameter for the first dwells and the revisit dwells. Error bars represent the standard error of the mean, triple Asterisks indicates $p < 0.001$.

relevance \times position interaction ($F(5, 95) = 4.67$, $p < 0.01$, $\eta_p^2 = 0.20$). Participants demonstrated higher dwell times on relevant vs. irrelevant parameters ($p < 0.001$ in all comparisons), except for the second dwell position ($p > 0.05$), as seen in Fig. 10.

The frequency of dwells on relevant parameters, presented in parentheses above each serial position, was above chance level at each of the six dwell positions. The chance level was 31.25%, for an average of 2.5 relevant parameters among the eight parameters per trial (in fact two or three relevant parameters per trial, representing 60 relevant parameters on a total of 192 parameters that contained the 24 trials that were associated with a rule). At the beginning of the decision-making process, 37% of the first dwells were oriented towards a relevant parameter. After that, the probability to gaze a relevant parameter increased considerably, in particular during the last three dwells, reaching 69% for the last dwell, see Fig. 10. We conducted a one-way repeated measure ANOVA, using the position of dwells as the independent variable and the probability to dwell a relevant parameter as the dependent variable. The ANOVA confirmed a significant main effect

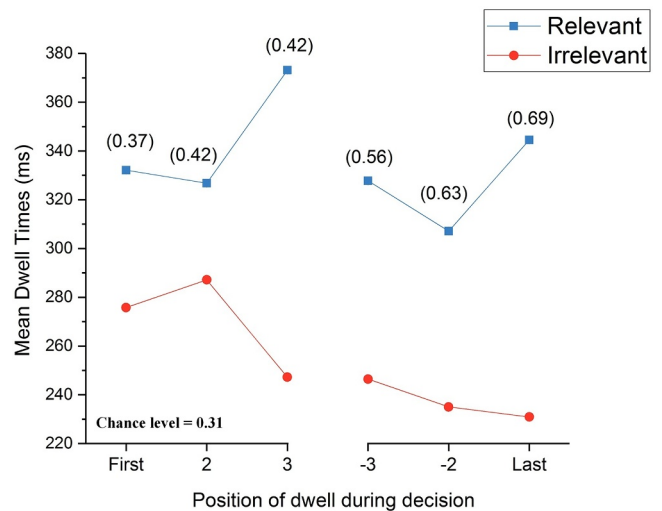


Fig. 10. Dwell sequence analysis for the first three dwells and the last three dwells prior decision. Lines represent mean dwell times (i.e. average dwell time of each unique consultation) on relevant and irrelevant parameters. The dwell frequency is presented in parentheses above each position. It represents the proportion of trials (among the 24 trials in which a rule was applicable) in which a relevant parameter was gazed at this dwell position (chance level = 0.31).

of the serial position of dwell on the probability to dwell a relevant parameter ($F(5,95) = 22.20$, $p < 0.001$, $\eta_p^2 = 0.54$). The Tukey's HSD post hoc test revealed a higher probability to dwell a relevant parameter during the last three dwells compared to the first three dwells (all $p < 0.01$), and during the last dwell compared to the third last (-3) ($p = 0.01$). No difference between the second last (-2) and the last dwell was found.

4. Discussion

4.1. General discussion

In dynamic environments such as ATC, human operators must constantly monitor and integrate incoming information in order to make optimal decisions. Today's increase of aircraft traffic challenges not only airport infrastructure but also the operators' cognitive capacities. However, developing a fully automatic system to support humans can be sub-optimal without integrating human expertise, knowledge of unknown rules, preferences, and situation awareness. We proposed an ATC route suggestion system that takes into account both the participant's decisions and fixation times on crucial parameters displayed at the screen. As expected, the suggestions were improved by the integration and weighing of the user's previous decisions. Importantly, determining the critical information for the decision-maker with eye-tracking helped to further improve the DSS suggestions. The key point of the introduction of eye data in the algorithm was the capacity to automatically discriminate relevant (i.e. relevant for the decision because involved in a given rule) from irrelevant parameters on the basis of the total dwell duration. This result is related with past studies that showed systematic "gaze bias" toward the chosen or preferred item (Glaholt and Reingold, 2009; Schotter et al., 2010). Parameters that were subjected to longer fixations received higher weights, which allowed the system to understand the operator's decisions quicker in comparison to the sole integration of previous decisions. Since the operator was confronted with numerous parameters, the number of possibilities that could explain a decision was high. Therefore, the learning phase of the algorithm is much more complex when considering all parameters uniformly. Eye-tracking data helped reducing the amount of data required for the training of the classifier and the historic based route suggestion. In the distance function, useful parameters received a higher weight than parameters that were not/less gazed. As a consequence, it allows reducing the number of situations to explore before reaching an acceptable classification performance. To the authors' knowledge, this study is amongst the first research that assessed the possibility to increase suggestion relevance from a DSS with eye-tracking. Previous studies did use ocular data to read decision-making with a real-time perspective, but this was done to modify the participant's decisions, and not to better adapt a system (Pärnamets et al., 2015).

In order to better understand the dynamics of decision-making, we also examined how the fixations evolved over time. Our results revealed that mean dwell times on relevant parameters remained significantly higher during almost the entire decision process, whereas the probability to dwell relevant parameters was particularly important during the few last dwells prior to choice. These results support the idea that the decision-making process can be partitioned into distinct stages, i.e. an initial screening stage followed by a more thorough evaluation of the few remaining alternatives (Biehal and Chakravarti, 1986; Lussier and Olshavsky, 1979). In this sense, Russo and Leclerc (1994) reported longer mean dwell times on the chosen item all throughout the entire decision-making process (from the first dwell to the last dwell prior to the choice) whereas the probability to dwell on a chosen item was higher only in revisit dwells vs. first dwells. Despite the difference in paradigm, our results followed a similar trend with relevant items being gazed at for a longer

duration throughout the entire decision-making process and with higher frequency of visits especially for the final dwells. More generally, the number of fixations reflects the importance of an interface object to the participant (Bednarik, 2005), and the eye-mind assumption (Just and Carpenter, 1980) posits that there is no lag between what the observer is fixating on and what the mind is processing. This latter theory also posits that fixation duration reflects the time to execute comprehension processes. Even if the link between the gaze and cognitive process may not be so strong, for example, the mind may be sometimes "ahead" of the eyes (Everatt and Underwood, 1992), or fixations does not necessarily indicate that information is processed (Simons and Chabris, 1999), it is reasonable to state that eye movements are not random and that there is an important relationship between eye movements and visual attention. Thus, we suggest that the combination of dwell times during the entire decision-making process, with dwell frequencies in the last moments of the decision, seems to be a promising metric to better read the decision process in the human's eye and could be very useful to improve system adaptation.

4.2. Limitations

While the designed experiment reproduced several ATCO operations, there were limitations in its ecological validity. First, the nature of the sample, consisting of 22 participants who were not qualified ATCOs; second, the fact that the experimental paradigm was simplified and not identical to a real ground traffic management environment. We integrated eight key parameters whereas real life settings take into account many more variables. Moreover, we did not integrate other vehicles in the route suggestions, i.e. conflict between aircraft was not considered. Equally though, the simulation lasted less than 30 minutes while operator performance may decrease over longer period due to a vigilance decrement, and these may be interesting points for future research. Our ATC-like synthetic environment was designed to provide an optimal balance between ecological validity and experimental control. This simplified context allowed recruiting participants without professional ATC qualification. Indeed, with only a basic ATC knowledge, our participants were all able to understand and perform the simulation without much difficulty. At a more advanced stage, it would be necessary to confirm our results using a more complex and realistic simulation and with ATCOs participants. Such an experiment will more closely assess the benefit of exploiting behavioral and eye-tracking measures with a specialized population that has developed heuristics and expert strategies. Despite these limitations, we believe that our experiment constitutes a valuable proof of concept of the use of eye-tracking as input for system adaptation.

4.3. Perspectives and conclusion

The aim of this research was to implement an adaptive system that takes into account both previous actions and eye fixations on the interface. We explored the use of real-time eye-tracking to understand decisions and cognitive processes to enhance an adaptive system. Eye-tracking shed light on features of the interface that were visually inspected, and on the strategies exhibited by the user (Bednarik, 2005). Indeed, objects under visual investigation are most likely located on the top of the cognitive processing stack, thus giving a reliable indication on features of the interface that are currently interesting and important for the user. By giving more importance (higher weights) to the parameters that were fixated during a longer period of time during the decisions, the system was able to enhance its capacity to understand human decisions, after which it could improve the accuracy of its future suggestions. Our results also support the idea that the dynamics of the decision-making process generates two types of visual behavior, with a first "screening" stage in which relevant stimuli are subjected to longer

dwell times, and a later “scrutinizing stage” resulting in more frequent fixations on relevant items. Using gaze behavior as a real-time adaptation source is promising. Our work offers a preliminary basis, arguing in favor of the need to develop new adaptive systems that integrate human actions and objective measures such as eye data. Lastly, contrary to more cumbersome and invasive tools that are often used to evaluate the mental state of the operator (e.g. electroencephalography, electrocardiography, etc.), “Eye-Computer Interfaces” (ECI) do not necessarily require the user to wear a device, at least in the case of remote eye-tracking, and has the advantage of offering a direct access to visual attention processes.

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