Introduction for ATC Experiment E1

R. Boag

Introduction

For the past 50 years, much psychological research on decision-making has used two-alternative forced-choice (2AFC) tasks to explore decision-making behavior and make theoretical inferences about the latent cognitive processes that drive performance (Laming, 1968; Link & Heath, 1975; McClelland, 1979; Stone, 1960; for reviews see Bogacz, Brown, Moehlis, Holmes, & Cohen, 2006; Ratliff & Smith, 2004). In a typical 2AFC task, decision-makers are presented with a series of stimuli about which a decision or response must be made (e.g., is this letter string a word?; is this arrow pointing left or right?). Conventionally, performance on these kinds of simple decision-making tasks had been analysed by comparing mean response time (RT), mean accuracy, receiver operating characteristic (ROC) curves (Swets, 1973), or methods related to signal detection theory (SDT; Green & Swets, 1974).

However, the biggest theoretical and practical advances in decision-making research have stemmed from the development of sequential-sampling models (Forstmann, Ratcliff, & Wagenmakers, 2016). Sequential-sampling models are a class of computational process model which formalise the latent cognitive processes theorised to underlie decision-making. When fit to data, such models provide a full quantitative account of both RT distributions and the accuracy of decisions. The central feature of sequential-sampling models is that decision-making is conceptualised as a process of taking repeated samples of information from the environment until enough evidence has been obtained to trigger a response or action. Although there are many such models, which can differ on numerous dimensions (e.g., linear vs nonlinear accumulation; independent vs dependent accumulation, fixed-rate vs decaying accumulation, static vs collapsing response thresholds, and so on; Hawkins, Forstmann, Wagenmakers, Ratcliff, Brown, 2015; Smith, 2010; Usher & McClelland, 2001; Vickers, 1970), models typically give convergent theoretical interpretations when fit to the same data (Donkin, Brown, Heathcote, & Wagenmakers, 2011; Heathcote & Hayes, 2012). Two of the most successful and widely applied of these models are the Ratcliff Diffusion Model (DM; Ratcliff, 1978; Ratcliff & Rouder, 1998), and the Linear Ballistic Accumulator (LBA; Brown & Heathcote, 2008), described below.

Ratcliff's (1978) diffusion model is perhaps the most influential and widely applied evidence accumulation model (Ratliff & Smith, 2004). The DM formalises decision-making as a process of noisy evidence accumulation. Evidence is sampled sequentially over time in a noisy diffusion process until evidence for one response or another crosses a predetermined response boundary which determines the overt choice. The DM models tasks in which a rapid choice between two response alternatives must be made, such as brightness discrimination or lexical decision tasks. The core components of the DM are: the speed or quality of evidence processing, which is quantified by the drift rate parameter; the response criterion or threshold, quantified by the distance between response boundaries; and the nondecision time parameter, which quantifies aspects of processing that fall outside of the accumulation process such as stimulus encoding and motor response time. Several other parameters represent variability in the mean rate and starting point of the diffusion process, and a bias parameter is sometimes used to quantify response biases between different alternatives.

The Linear Ballistic Accumulator (Brown & Heathcote, 2008) differs from the DM in that the decision process is modelled by independent racing accumulators with in which evidence is sampled linearly, rather than a noisy diffusion process wandering between two response boundaries. As such, the LBA is easily extended to tasks involving more than two response alternatives, and the absence of non-linear diffusion makes it more computationally tractable. In the LBA, evidence for each response accrues linearly in separate accumulators, with processing speed or quality quantified by the accumulation rate parameter (analogous to drift rate in the DM). Each LBA accumulator has its own response boundary or threshold, nondecision time, accumulation rate starting point and variabilty parameters. By evaluating which parameters can remain fixed and which must be allowed to vary over experimental conditions, theoretical inferences can be drawn about the latent cognitive processes that underlie decision-making in various tasks and under various conditions (Donkin, Brown, & Heathcote, 2011).

The LBA and DM have yielded important theoretical insights in a wide range of basic and applied domains, including attention and working memory (Sewell, Lilburn, & Smith, 2016), recognition memory (Ratcliff, 1978), workload capacity (Eidels, Donkin, Brown, & Heathcote, 2010), bilingualism (Ong, Sewell, Weekes, & McKague, 2017), sleep deprivation (Ratcliff & van Dongen, 2011), alcohol and drug use (van Ravenzwaaij, Dutilh, & Wagenmakers, 2012), clinical disorders (Moustafa, Kéri, Somlai, Balsdon, Frydecka, Misiak, & White, 2015; White, Ratcliff, Vasey, & McKoon, 2010), consumer choice (Hawkins, Marley, & Heathcote, 2014; Trueblood, Brown, & Heathcote, 2014), and applied aviation and defense research (Palada, Neal, Vuckovic, Martin, Samuels, & Heathcote, 2016; Vuckovic, Kwantes, Humphreys, & Neal, 2014).

However, most tasks analysed with these models have been basic cognitive or psychophisiological tasks (e.g., perceptual discrimination) in which decisions typically unfold over very short timescales (i.e., less than 1 to 2 seconds) and with perceptually simple, static stimuli (e.g., gabor patches, letter strings, or simple geomteric shapes). Although such tasks and the associated modelling results have provided many important insights into cognitive and perceptual processes, these tasks have limited generalisability to more applied settings in which decisions often unfold over much longer timescales, stimuli are often more complex and change dynamically over time, and where external environmental variables such as time pressure, task load, and addtional memory demands often dictate how an operator must approach a given task (Loft, 2014). Given the growing applied and human factors interest in formal models of human performance (Byrne & Gray, 2003; Schweickert, Fisher, & Proctor, 2003), an important goal is the development of models that properly characterise the cognitive processes involved in complex applied tasks and can provice accurate predictions regarding performance under different circumstances (Dismukes, 2008).

In the field of air-traffic control (ATC), for example, controllers are responsible for ensuring the safe and efficient passage of aircraft through a sector of airspace (Durso & Manning, 2009). To this end, controllers must continuously monitor multiple aircraft, which enter and exit the display at different times, and which vary on a number of critical spatial variables such as airspeed, flight level (altitude), climb rate, and heading. In addition, controllers are often required to monitor changing weather conditions, respond to pilot requests, and ensure aircraft maintain adequate lateral and vertical separation (Durso & Manning, 2009). This degree of task complexity is representative of that faced by operators in a wide variety of applied, safety-critical settings, including submarine track management (Loft, Bowden, Braithwaite, Morrell, Huf, & Durso, 2015) and the operation of unmanned aerial vehicles (UAVs; Palada, Neal, Vuckovic, Martin, Samuels, & Heathcote, 2016).

Although these tasks share some similarities with basic lab paradigms (e.g., both UAV and perceptual vigilance tasks involve detecting targets), their level of complexity is clearly very different, which may have implications for our ability to create models of these kinds of tasks. As such, an important research goal is to establish whether such models can be applied to more complex, dynamic, 'real-world' tasks such as ATC in which operators must deal with frequent changes in both display stimuli and aspects of the task environment (Loft, 2014). Importantly, if such tasks can be modelled appropriately, these models may be able to provide valuable insights regarding how people perform these tasks, the strategies they use, and what cognitive processes that drive changes in performance. In addition, insights from model-based analyses be used to inform applied and human factors research regarding practical issues such as task design, training, and the development of decision aids (Dismukes, 2008).

This study aims to address this gap by extending the LBA model to a complex dynamic ATC task representative of a broad set of applied tasks common to many work settings. We aim to evaluate the impact of two of the most common external enivironmental variables that commonly impact tasks in applied settings: time pressure, and prospective memory (PM) demands. Finally, we demonstrate the usefulness of our modelling approach in illuminating the latent cognitive processes that drive task performance and how such processes change in response to different environmental conditions (time pressure and PM demand). Thus showing the utility of this approach in answering both theoretical and applied questions. The following section outlines some potential issues with applying a model of simple choice such as the LBA to a more complex and dynamic task.

Assumptions of Evidence Accumulation Models and Issues with Modelling Complex Tasks

One reason models of simple choice like the DM and LBA have not seen wide application to more complex decision-making tasks is that the architecture of the models contain certain assumptions about the nature of the cognitive processes driving each decision - assumptions which must be met in order for the models to fit data and provide valid theoretical interpretations (Lerche & Voss, 2017; Ratcliff, 2002; Voss, Nagler, & Lerche, 2013). One assumption with implications for applied tasks is that models assume decisions are the result of a relatively 'pure' evidence accumulation process (i.e., a single continuous stage of information integration; Smith, 2000; Vanderkerckhove & Tuerlinckx, 2007) in which responses are made very quickly (usually within 1 second). This differs from many real-world settings where multiple sources of information must be integrated to form a decison, and where decisions often unfold over much longer timescales (e.g., 2-10 seconds). Long decisions are less likely to be the result of continuous uninterrupted sampling and are more likely to be contaminated by other processes such as double-checking, distraction/mind-wandering, interruptions, and attention-switching which are not accounted for in standard choice models. Relatedly, the models typically assume that only a single stimulus or source of evidence is considered at a time. This differs from many applied tasks which can have multiple relevant stimuli on display at the same time - all of which could contain decision-critical information and which therefore must be processed simultaneously.

Perhaps most important for complex applied tasks is that the models assume all information is processed in parallel rather than in a sequentially. This assumption is critical for fitting the models to data and is also arguably the most likely assumption to break down in tasks involving multiple dynamic stimuli. In air-traffic control tasks, for example, operators may scan sequentially between stimuli as well as between other on-screen items (e.g., timers, scale markers) multiple times before making a response. These kinds of serial decision-making strategies produce RT distributions with very different shapes than those produced by parallel decision-making strategies (Palada, et al., 2016), which may result models being unable to fit data (Ratcliff, 2002; Heathcote, Wagenmakers, & Brown, 2014). In other words, complex, multi-stimulus tasks may encourage different strategies (e.g., serial processing, partial processing, double-checking, etc.) or rely on different cognitive mechanisms (e.g., response competition or interference, nonlinear or piecewise accumulation, evidence decay, urgency signals/collapsing thresholds, etc.) than those involved in simpler decision-making tasks. Any model that does not include those processes will therefore be a poor descriptive model of the task and likely be unable to fit empirical data from the task.

Another issue is that models such as the DM are not easily extended to decisions involving more than two response alternatives (Forstmann, Ratcliff, & Wagenmakers, 2016). Being restricted to modelling two-alternative tasks limits applicability to many applied tasks in which decisions often involve many more than two options. Parallel race models like the LBA, however, are easily extended to tasks with any number of response alternatives, without loss of analytic tractability (Brown & Heathcote, 2008). A final point relates to the computational tractability of models in terms of fitting them to data. Both the DM and LBA are extremely costly to fit in terms of time and computing power, and these costs increase exponentially as the complexity of models to be fit increases (some models with nonlinear accumulation processes cannot be fit to data at all). This is not so much a limitation of the models themselves, but it is a factor that can severely limit the complexity of tasks to which these models are applied and the complexity of experimental designs which can be analysed with these models. To summarise, complex, dynamic applied tasks may differ in important ways from the basic lab paradigms for which models of simple choice were originally designed and validated. Specifically, if the cognitive strategies and/or processes used to perform more complex tasks are very different from those used in simpler decision-making tasks, then models of simple choice will be the wrong models of the processes involved in complex tasks and produce poor fits to empirical data. Neverthless, several recent studies have had some success in applying these models to more complex tasks (Palada, et al., 2016). The following section describes some recent attempts to model complex dynamic tasks with simple-choice frameworks and outlines the architecture of our model of a dynamic ATC conflict detection task.

Modelling a Complex Dynamic Task: A Model Architecture

To-date there have been several attempts to model more complex applied tasks with evidence accumulation models like the DM and LBA (Diederich, 1997; Eidels, Donkin, Brown, & Heathcote, 2010; Hawkins, et al., 2014; Little, Nosofsky, & Denton, 2011; Little, Nosofsky, Donkin, & Denton, 2013; Palada, et al., 2016; Trueblood, Brown, & Heathcote, 2014: Vuckovic, Kwantes, & Neal, 2013; Vuckovic, Kwantes, Humphreys, & Neal, 2014).

For example, Palada et al. (2016) used LBA accumulators to model a dynamic UAV target classification task in which up to five stimuli appeared on screen at a time, stimuli contained multiple attributes relevant to each decision, and stimuli had asynchronous onset and offset times on the display. Participants performed the task under different levels of time pressure, workload (number of ships on screen), and with varying degrees of dynamic pixel noise affecting the quality of the visual display. Despite the highly dynamic nature of the task and the complexity of the decision, their LBA-based model provided a close fit to data and reproduced the benchmark effects of their experimental manipulations (i.e., lower thresholds under high time pressure, lower drift rates under high pixel noise, lower drift rates for more difficult stimuli).

Likewise, Vuckovic, Kwantes, Humphreys, & Neal, (2014) developed a sequential-sampling framework to model how ATC conflict detection performance varied with time pressure (speed vs accuracy instructions) and the difficulty of aircraft stimuli (e.g., by varying speed, distance, approach angle). Their model used specific spatial properties of on-screen aircraft such as airspeed and approach angle to predict the rate of evidence accumulation. The model showed good fits to data and provided parameter estimates with sensible psychological interpretations of threshold and accumulation rate changes consistent with those found in studies of simpler tasks.

Although these studies have had success in modelling complex tasks with dynamic, multi-attribute stimuli, the models often employed complex architectures with highly task-specifc inputs (e.g., spatial properties of on-screen aircraft) which do not generalise easily to other applied contexts, highly specialised expiremental designs not easily adapted to applied settings (e.g., Townsend & Nozawa, 1995), and rich parameterisations requiring large amounts of data and computational resources to fit. In addition, none of the aforementioned studies looked at complex tasks involving additional PM demands. As such, there is no computational model of a complex dynamic task that accounts for PM performance in addition to the primary ongoing task.

There have however been several studies that used DM and LBA frameworks to model PM in basic lab paradigms (Boywitt & Rummel, 2012; Heathcote, Loft, & Remington, 2015; Horn & Bayen, 2015; Horn, Bayen, & Smith, 2011; Strickland, Heathcote, Remington, & Loft, 2017, Strickland, et al., 2017). These studies have provided a more detailed analysis of the cognitive processes that underly PM than has been possible with conventrional analsyes of RT and accuracy. However, the models have almost exclusively only been fit non-PM trials rather than the full array of PM data, and as such do not provide a complete account of PM effects (Boywitt & Rummel, 2012; Heathcote, Loft, & Remington, 2015; Horn & Bayen, 2015; Horn, Bayen, & Smith, 2011; Strickland, Heathcote, Remington, & Loft, 2017; see Strickland, et al., 2017 for the an exception).

Rather than attempting to develop more a more complex, task-specific model (e.g., Corker, Gore, Fleming, & Lane, 2000; Eyferth, Niessen, & Spaeth, 2003; Leiden, Kopardekar, & Green, 2003; Neal & Kwantes, 2009; Niessen, Eyferth, & Bierwagon, 1999), our goal here was to evaluate whether a standard choice model with a flexible parameterisation could provide an adequate description of data from a complex and dynmamic task respresentative of those performed in many applied settings. Following Palada et al. (2016) and Strickland et al. (2017) we used LBA accumulators to model decision-making in a complex dynamic ATC conflict detection task with both time pressure and PM demands. Our model architecture includes three LBA accumulators: two that correspond to the ongoing task responses (i.e., conflict/nonconflict), and a third that corresponds to the PM response. In the model, stimulus features consistent with a particular response provide excitatory input to the corresponding accumulators, as well as possibly providing inhibitory inputs to the other accumulators. The evidence total in each accumulator increases independently of the evidence totals in other accumulators, and the first accumulator to reach its threshold determines the response made.

Figure XX depicts the model for a single conflict detection decision task with a concurrent PM task requirement. There are three possible response alternatives, which correspond to indicating that the stimulus is either a *conflict*, a *nonconflict*, or a *PM target*. Evidence for each response accrues linearly towards threshold, starting from a point that varies independently between accumulators from trial to trial according to a uniform distribution. Correct PM responses (PM hits) occur on PM trials when the PM accumulator reaches threshold before either of the ongoing task (conflict/nonconflict) accumulators. Similarly, PM misses occur when one of the ongoing task accumulators finishes before the PM accumulator. Response probabilities vary depending on the values of three classes of model parameters related to the level of start-point variability and thresholds and evidence accumulation rates. Evidence accumulates at a constant rate within a given trial, but rates differ from trial to trial according to a normal distribution. Accumulation rate parameters are usually assumed to vary as a function of stimulus differences and can vary from trial to trial. Thresholds parameters, in contrast, are set prior to stimulus presentation, and are unaffected by stimulus characteristics that vary unpredictably from trial to trial. However, thresholds can vary over blocked manipulations (e.g., PM vs control blocks; high vs low time pressure), and by response (e.g., a less conservative threshold might be set for 'conflict' responses compared to 'nonconflict' responses). The level of start-point variability is assumed not to vary over the conditions we examine here, although it might vary in other circumstances. Decision time (i.e., the time for the winning response to accumulate to threshold) is determined by the same set of parameters as response probabilities. Total RT is determined by decision time plus nondecision time, which includes all nondecisional processes, such as stimulus encoding and motor response production. Nondecision time was assumed to be the same across all experimental conditions and all response accumulators. Thus we estimated only one nondecision time parameter.

Importantly, this modelling framework will allow us to test the ability of the LBA to model more complex decisions than it has as yet been applied to, and, assuming good fit, to interpret the underlying cognitive mechanisms driving performance and how they may be affected by changes in time pressure and PM demand. By evaluating model fit, we can determine whether the basic assumptions (i.e., a parallel independent race with feedforward excitation and inhibition and linear updating) are sufficient to model the processes driving performance in this more complex, dynamic, multi-stimulus applied task. Misfit will suggest that this architecture may not be the correct process model of our more complex task. Misfit will suggest that different strategic (e.g., serial processing, double-checking) or cognitive mechanisms (e.g., nonlinear or piecewise accumulation, collapsing thresholds) may need to be added to the model in order to adequately capture performance. Nevertheless, assuming a sufficiently good fit, the way in which model parameters vary to capture the effects of time pressure and PM demand will allow us to evaluate the latent cognitive processes that drive observed responding in this complex, dynamic, multi-stimulus ATC task. The following sections describe the benchmark effects of time pressure and PM demand manipulations, theoretical predictions, and how the proposed model will distinguish between competing theories

Decision-Making under Changing Task Conditions: Time Pressure and PM Demand

This section reviews the effects of time pressure and PM demand - two factors that commonly impact decision-making in applied settings - on task performance. We review the benchmark effects of time pressure and PM demand on task RT and accuracy, and discuss cognitive theories that have been proposed to explain these effects.

Time Pressure and the Speed-Accuracy Trade-Off

Human decision-making almost always occurs under some form of time pressure (Svenson & Maule, 1993). Time pressure refers to constraints on the time available to gather information and deliberate before committing to a response or course of action. Time constraints can be internal, in which the decision to stop deliberating and execute a response or action is self-imposed, or external, in which the time available for deliberation is limited by aspects of the task itself (e.g., tasks in which decisions must be made before a deadline) or changes in the task environment (e.g., when increased workload requires more decisions to be made per unit time; Wickelgren, 1977).

Time constraints are extremely prevalent in every day life and work settings (e.g., deciding on the right moment to merge into traffic; being given a shorter deadline within which to complete a work task), and can affect both the speed and quality with which tasks are performed and decisions made (e.g., having too little time to weigh up all the evidence before committing to a decision; Stokes, Kemper, & Kite, 1997). Increases in time pressure have been implicated in poorer safety outcomes in many safety-critical settings, including road-safety (Gelaua, Sirek, Dahmen-Zimmer, 2011; Shinar, 1998) and aviation (Sarter & Schroeder, 2001).

The effects of time pressure on decision-making are typically studied in experiments that manipulate either the absolute time available for decisions (i.e., by imposing different response deadlines; Frazier & Yu, 2008; McElree & Dosher, 1989; Meyer Irwin, Osman, & Kounios, 1988) or which vary the subjective importance of fast versus accurate decisions via task instructions or by providing incentives that reward either fast or accurate task performance (Milosavljevic, et al., 2010). Importantly, changes in time pressure have systematic effects on RT and accuracy. Higher time pressure (i.e., less deliberation time) generally leads to faster but less accurate decisions, whereas lower time pressure (i.e., more deliberation time) leads to slower but more accurate decisions. This phenomenon is known as the speed-accuracy trade-off (SAT; Wickelgren, 1977), and has been the subject of much computational cognitive modelling (Dutilh, Wagenmakers, Visser, & van der Maas, 2011; Forstmann, Tittgemeyer, Wagenmakers, Derrfuss, Imperati, & Brown, 2011; Usher, Olami, & McClelland, 2002) and neuropsychological research (Bogacz, Wagenmakers, Forstmann, & Nieuwenhuis, 2010; Heitz & Schall, 2012, Heitz, 2014).

In terms of formal cognitive theories, the SAT is typically implemented in computational decision models by including a variable response threshold or decision boundary that varies over different levels of time pressure (Ratcliff & Rouder, 1998). By setting a higher (i.e., more conservative) response threshold, operators can choose to gather more evidence or deliberate for a longer period of time before committing to a response, thus producing the characteristic slow-but-accurate response pattern. Conversely, by setting a lower (i.e., less conservative) response threshold, operators spend less time deliberating and gathering evidence, and are therefore able to make faster responses (albeit at the expense of accuracy).

Indeed, allowing the threshold parameter alone to vary across time pressure conditions is often sufficient to allow choice-RT models to closely fit empirical SAT data (e.g., Forstmann, et al., 2008; Ratcliff, 2002; Ratcliff & Rouder, 1998; Ratcliff, Thapar, & McKoon, 2003; Thapar, Ratcliff, & McKoon, 2003; Wagenmakers, Ratcliff, & McKoon, 2008). In contrast, time pressure generally has minimal effect on more automatic decision processes such as accumulation rates and the nondecisional components of response time such as encoding and motor response time (i.e., fixing these parameters has little effect on how well models fit empirical data). Because response thresholds are assumed to be under the conscious control of the decision-maker, these findings suggest time pressure primarily leads operators to make deliberate, proactive adjustments to their response thresholds; responding more conservatively under low time pressure to increase accuracy and less conservatively under high time pressure to increase speed. In other words, time pressure primarily influences a strategic, proactive component of the decision-making process under the conscious control of the operator.

It should be noted however that time pressure may also influence the quality of evidence accumulation (i.e., accumulation rates; Heathcote & Love, 2012; Heitx & Schall, 2012; Ho, Brown, van Maanen, Forstmann, Wagenmakers, & Serences, 2012; Rae, et al., 2014; Starns, Ratcliff, & McKoon, 2012;

Vanderkerckhove, Tuerlinckx, & Lee, 2008), nondecision time (Dambacher & Hubner, 2015), and variability in the rate of evidence accumulation (Milosavljevic, et al., 2010). In terms of accumulation rates, the aforementioned studies have suggested that in addition to threshold shifts, time pressure may reduce the quality of evidence entering the decision process (i.e., lower accumulation rates) and increase the variability in accumulation rates reflecting greater noise in the accumulation process (Milosavljevic, et al., 2010). Time pressure may also shorten nondecision time, by speeding up motor response processes (e.g., Dambacher & Hubner, 2015; Osman et al., 2000; Rinkenauer et al., 2004; van der Lubbe et al., 2001), or by increasing temporal preparation, which has been shown to lead to earlier onset times for evidence accumulation processes (Bausenhart, Rolke, Seibold, & Ulrich, 2010; Seibold, Bausenhart, Rolke, & Ulrich, 2011), or by decreasing the frequency of 'double-checking' for stimuli (Boywitt & Rummel, 2012; Guynn, 2003; Horn, Bayen, & Smith, 2011).

In contrast, studies on mind-wandering suggest that accumulation rates may increase rather than decrease with time pressure (McVay & Kane, 2009; Rummel, Smeekens, & Kane, 2016; Smallwood, 2013; Smallwood & Schooler, 2015). Specifically, more difficult task conditions (e.g., high time pressure) tend to lead to less mind-wandering and increase task focus because participants engage in fewer task-unrelated thoughts while performing the task (Kane & McVay, 2012; Rummel, Smeekens, & Kane, 2016). In the model, task focus maps naturally onto the accumulation rate parameter. As such, if time pressure increases task focus by reducing mind-wandering, we would expect higher accumulation rates in high time pressure blocks compared to low time pressure blocks. Considering that our ATC task is more resource-demanding than the basic tasks used in these studies (e.g., lexical decision) people may be already maximally focused even during low time pressure blocks. As such, it may be more plausible here for time pressure to negatively affect the quality of information processing (i.e., accumulation rates), since participants may already be committing their full compliment of cognitive resources to the task. Nevetheless, given the novelty of our task, these possibilities are both plausible and will be explored further in our computational modelling.

Event-Based PM Demand and PM Cost

In addition to time constraints, much real-world decision-making is performed under prospective memory demand (Dismukes, 2012). Prospective memory refers to the formation and maintenance of intentions to perform future actions - actions which cannot be completed immeditately and must be deferred either until a later point in time (i.e., *time-based PM*; Park, et al., 1997) or until a particular future event or stimulus is encountered (i.e., *event-based PM*; Brandimonte, Einstein, & McDaniel, 1996; Einstein & McDaniel, 1990; Ellis & Cohen, 2008; Kliegel, McDaniel, & Einstein, 2008). The period between encoding and executing PM intentions is usually filled with one or more ongoing tasks unrelated to the intention, which typically must be retrieved and executed in the absence of an explicit reminder (Dismukes, 2012).

Event-based PM task requirements are highly prevalent in everyday life (e.g., remembering to send an email once you arrive at work, remembering to take food out of the oven), and can have important satefy implications (e.g., remembering to clear one aicraft off the runway before allowing another to land; National Transportation Safety Board, 1991; remembering to slow down while driving through a school zone; Bowden, Visser, & Loft, 2017). In aviation research, for example, addtional PM demand has been implicated in operators being slower to accept and handoff aircraft, slower to detect conflict between aircraft, as well as increased rates of missed conflicts (Loft, Finnerty & Remington, 2011; Loft, Pearcy, & Remington, 2011; Loft & Remington, 2010; Loft, Smith, & Bhaskara, 2011; Loft, Smith, & Remington, 2013; Loukopoulos, Dismukes, & Barshi, 2009). Reliable retrieval and execution of PM intentions is therefore crucial safety-critical decision-making contexts including aviation, medicine, and defence (Dembitzer & Lai, 2003; Dismukes, 2012; Gawande, Studdert, Orav, Brennan, & Zinner, 2003; Grundgeiger & Sanderson, 2009; Loft, 2014). Importantly, because operators may perform many thousands of actions under PM load per day, even small PM error probabilities have the potential to translate into significant accident rates (Dismukes & Nowinski, 2006; Shorrock, 2005). As such, it is critical that models of applied tasks properly account for the effects of concurrent PM task demand on operator performance.

The effect of PM demand on decision-making is typically studied in experimental paradigms in which an infrequently-occurring PM task is embedded within a primary 'ongoing' task (Einstein & McDaniel, 1990). For example, a common ongoing task used to study PM is the lexical decision task, in which participants must decide whether letter strings are words or not. Prior to performing the task, participants are instructed to make an atypical PM response (e.g., press 'F1') if they encounter a PM target (e.g., any words related to the category 'animal'). Participants typically complete both a control block in which the ongoing task is performed by itself with no PM requirement, and a PM block in which the ongoing task is performed concurrently with the embedded PM task. Ongoing task performance can then be compared with and without PM demand (Smith, Hunt, McVay, & McConnell, 2007).

The benchmark finding in the PM literature is that ongoing task RTs are typically longer in PM blocks compared to control blocks. That is, people make slower ongoing task responses when required to hold concurrent PM intentions, a phenomenon known as *PM cost* (Einstein et al., 2005; Hicks, Marsh, & Cook, 2005; Loft & Yeo, 2007; Smith, 2003). PM costs have been used to infer the cognitive processes that underlie PM performance as well as those believed to drive observed ongoing task costs. For example, capacity-sharing theories of PM costs (Craik, 1986; Marsh & Hicks, 1998; Park, Hertzog, Kidder, Morrel, & Mayhorn, 1997) attribute PM costs to some limited-capacity cognitive resource (e.g., prepatory attention, monitoring) being shared between the ongoing and PM tasks (Boywitt & Rummel, 2012; Einstein & McDaniel, 2005; Smith, 2003). That is, the processes responsible for holding PM intentions and/or monitoring for PM targets are assumed to draw cognitive resources away from the ongoing task, thereby reducing the efficiency with which the ongoing task can be performed (Smith, Hunt, McVay, & McConnell, 2007). In terms of evidence accumulation models, processing efficiency maps naturally on to the drift rate or evidence accumulation rate parameters. Computationally then, the capacity-sharing account attributes PM costs to a bottom-up, stimulus-driven reduction in ongoing task accumulation rates (i.e., less efficient processing) under PM load.

Another perspective, the Multiprocess View (MPV; McDaniel & Einstein, 2000; Einstein & McDaniel, 2005), argues that PM responses need not always draw resources away from the ongoing task (Kliegel, Martin, McDaniel, & Einstein, 2001). Specifically, the MPV claims that PM responses can also occur due to spontaneous retrieval as the result of cueing from ongoing task processes, and therefore do not necessarily require resources be redirected from the ongoing task. However, spontaneous retrieval would likely require some degree of similarity between the information used to make ongoing task and PM decisions, that is, spontaneous retrieval likely only applies to focal PM stimuli whose features are cued by the ongoing task, not to non-focal PM stimuli unrelated to the ongoing task. In the absence of spontaneous retrieval, the MPV also attributes PM costs to capacity-sharing (i.e., the diversion of resources from ongoing to PM task), which would be reflected in changes in the quality of evidence accumulation in models like the DM and LBA.

Standard capacity-sharing theories and the MPV have recently been challenged, however, by recent work showing that PM costs are primarily the result of strategic, metacognitive adjustments to the task environment rather than cognitive processing limitations (Heathcote, Loft, & Remington, 2015; Strickland, 2017). These theories (referred to here as *strategic delay* theories) argue that under PM load people set more conservative ongoing task response thresholds in order to avoid preepmting rare PM targets with the more common ongoing task responses. Setting more conservative ongoing task thresholds results in longer ongoing task RTs under PM load (i.e., PM costs), which facilitates responses to PM stimuli while maintaining comparable ongoing task accuracy between control and PM blocks (Strickland, 2017). That is, people may make similar strategic, proactive adaptations in response to PM demands as they do to different levels of time pressure. Other accumulation model parameters such as nondecision time are not typically implicated in PM processing (but see Boywitt & Rummel, 2012 who have argued that additional checking and/or encoding of PM stimuli may be reflected in a longer nondecision component; also see Guynn, 2003; Horn, Bayen, & Smith, 2011).

Proactive and Reactive Cognitive Control Mechanisms

In addition to top-down, deliberate control of thresholds in response to PM demand (referred to as *proactive control*), Strickland et al. (2017) found evidence of bottom-up or stimulus-driven inhibitory processes acting between PM and ongoing stimuli. These processes are known as *reactive control* and operate automatically rather than being under the decision-maker's conscious or deliberate control (Braver, 2012; Bugg, McDaniel, & Einstein, 2013; Ball, 2015). Specifically, Strickland et al. (2017) found that evidence accumulation rates for ongoing task responses were significantly lower on trials that also contained PM stimuli than on trials that did not contain PM stimuli, despite both trial types having equally strong evidence for the respective ongoing task response. They argued that although both PM and non-PM trials contained equal evidence for the ongoing task, on PM trials the ongoing task accumulators received inhibitory input from the PM detector, which reduced their rates of accumulation (Strickland et al., 2017). Because the presentation of PM stimuli was random, to which participants could not make deliberate anticipatory processing adjustments (e.g., to prepatory attention), reactive inhibition appears to be a largely automatic mechanism of decision control.

This finding, along with the benchmark effect of proactive threshold control, led Strickland et al., (2017) to frame their modelling results in terms of Braver's (2012) dual-mechanisms theory of cognitive control, which argues that human decision-making is subject to both proactive and reactive control mechanisms. Braver's (2012) theory has been useful for understanding cognitive control in many paradigms, including working memory tasks (e.g., Braver, Gray, & Burgess, 2007; Burgess & Braver, 2010; Marklund & Persson, 2012), the AX-Continuous performance task (e.g., Braver, Barch, Keys, et al., 2001; Locke & Braver, 2008; van Wouwe, Band, & Ridderinkhof, 2011), the stop signal task (e.g., Stuphorn & Emeric, 2012; Boehler, Schevernels, Hopf, Stoppel, & Krebs, 2014), the Stroop task (e.g., Kalanthroff, Avnit, Henik, Davelaar, & Usher, 2015; West, Choi, & Travers, 2010), and the cued task-switching paradigm (e.g., Chevalier, Martis, Curran, & Munakata, 2015; Lucenet, Blaye, Chevalier, & Kray, 2014). Additional empirical support for the dual-mechanisms account comes from psychophysiological studies showing that proactive and reactive control mechanisms correspond to distinct patterns of brain activity (Braver, 2012; Irlbacher, Kraft, Kehrer, & Brandt, 2014; Appelbaum, Boehler, Davis, Won, & Woldorff, 2014). The following section briefly outlines proactive and reactive control mechanisms in terms of Braver's (2012) dual-mechanisms framework and their relevance to the present study.

Proactive Control

In Braver's (2012) framework, proactive control refers to processes used to "bias attention, perception and action systems in a goal-driven manner" (Braver, 2012, p. 2). Proactive processes are deployed deliberately, in an anticipatory manner. That is, they are activated in advance of the target stimulus or event so that they will already active when the target stimulus is encountered (Braver, 2012). Because they are assumed to be under conscious control, proactive control processes are likely to be deployed for entire blocks of trials rather than on a trial-to-trial basis (especially when trials are presented randomly and cannot be anticipated).

In terms of time pressure and PM demand, proactive control in response to these manipulations would be active on all trials within a time pressure or PM demand block (e.g., all high time pressure trials, all PM block trials). Importantly, because proactive control processes selectively map onto the threshold parameter in sequential sampling models, their effects can be separated out from other non-proactive processes that may have similar block-wise effects on RT and accuracy (e.g., capacity cost effects). For example, longer RTs under PM load (i.e., PM costs) are predicted by both capacity-sharing and strategic delay theories of PM cost. Although both theoretical processes may have similar effects on manifest RT, the proposed source of those effects is very different. Capacity theories attribute PM block slowing to poorer-quality information processing due to resources being diverted from the ongoing task - which in the model would be reflected in the rate of evidence accumulation. In contrast, delay theories attribute slowing to more cautious responding - the result of setting higher ongoing task thresholds to give the parallel PM accumulation process a better chance of reaching response selection (Heathcote et al., 2015; Loft & Remington, 2010). Although these two accounts are confounded in conventional analyses of mean RT, they can be identified in the present model-based analysis.

Reactive Control

In contrast to deliberate, proactive control mechanisms deployed in anticipation of task demands, Braver (2012) argues that there are also more automatic, stimulus-driven cognitive mechanisms that are deployed to influence responding "only as needed, in a just-in-time manner" (Braver, 2012, p. 2). These are referred to as reactive control mechanisms. Reactive control mechanisms are more automatic, 'bottom-up' cognitive processes and are largely assumed to be outside of conscious control. As such, reactive control processes can be deployed on a trial-to-trial (or stimulus-to-stimulus) basis; they are not restricted to entire blocks of trials.

In terms of PM tasks, reactive control processes would be activated on PM trials when a PM stimulus is present but remain inactive on non-PM trials when no PM stimuli are present. An example of a reactive control process that would facilitate PM responding is if ongoing task processing is inhibited when PM stimuli are present. This kind of inhibition would improve PM accuracy. Due to their automatic, stimulus-driven nature, reactive control processes map selectively onto the accumulation rate parameter in sequentially sampling frameworks. Comparing accumulation rate parameters between PM trials and non-PM trials (in PM blocks only) allows us to detect and quantify reactive control effects. Moreover, because reactive control predicts different rates for PM and non-PM trials, it can be distinguished from capacity sharing, which predicts lower accumulation rates on all PM block trials regardless of whether a PM stimulus was presented or not.

The foregoing discussion has mentioned many empirical effects related to time pressure and PM load, with several competing theoretical explanations, including capacity-sharing, proactive and reactive cognitive control, and effort/arousal or task focus effects. As discussed, conventional analysis of mean RT and accuracy, or analyses based on ROC or SDT methods would be in many cases unable to detect these effects, let alone distinguish between their potential theoretical explanations. However, our modelling framework, is equipped to detect and explain these effects if they are present. Our model is based on Strickland et al.'s (2017) PMDC architecture; a computational framework capable of giving a full account of both the stimulus-driven, reactive components of PM demand as well as the top-down, proactive aspects of performance under PM demand. Their model combines the LBA's evidence accumulation framework with Braver's (2012) dual-mechanisms theory of cognitive control. Most importantly, this framework is capable of detecting proactive and reactive control effects and distinguishing between capacity-sharing and strategic delay accounts of PM cost. Here we extend this model in order to characterise and quantify the effects of time pressure and identify either processing quality decrements (predicted by capacity-cost theories of time pressure) or processing quality improvements (predicted by several recent mind-wandering and task focus studies). The next section describes in detail how we propose to use our model to identify and test these effects in a complex, dynamic ATC task.

Testing Cognitive Control Mechanisms in a Complex Dynamic Task

This study tests the ability of our model (based on the PMDC architecture of Strickland et al., 2017) to provide full account of decision-making under time pressure and PM demand in a complex, dynamic air-traffic control task. To this end, we have several objectives. First, we evaluate whether the model is capable of fitting the full array of data across our time pressure and PM demand manipulations. Adequacy of fit will indicate whether the LBA assumption that PM and ongoing task decision processes compete in an independent race is reasonable in this complex applied task. Model misfit could also indicate that the LBA is the wrong model of each accumulation process. Indeed, this is a plausible scenario in applied tasks as complex and dynamic as ours, in which decision-making processes may operate differently than in basic cognitive and perceptual lab tasks. For example, because our ongoing conflict detection task is dynamic, meaning that stimulus evidence unfolds over time, the task may violate the core LBA assumption that evidence accumulates linearly within each trial. Nevertheless, given the breadth of successful applications of the LBA in a wide variety of basic and applied paradigms (e.g., Brown & Heathcote, 2008; Eidels, Donkin, Brown, & Heathcote, 2010; Forstmann et al., 2008; Matzke, Love, & Heathcote, 2017; Palada, Neal, Vuckovic, Martin, Samuels, & Heathcote, 2016; Provost & Heathcote, 2015), and recent work suggesting constant-rate models are good approximations even if accumulation rates do change within trials (Ratcliff, 2002; Ratcliff, Smith, Brown, & McKoon, 2016), this seems like a relatively unlikely possibility. Second, assuming we find good fit, we will interpret model parameters in order to evaluate how well the data are described by capacity sharing theories of PM cost versus PMDC and strategic delay theory accounts. This can be done in part by comparing control blocks to PM blocks (proactive control), and in part by comparing non-PM trials with PM trials (reactive control). Moreover, we will evaluate how thresholds and accumulation rates change with time pressure, and whether proactive control of thresholds interacts with time pressure in any way.

Our approach to modelling and analysis deviates from traditional methods used in the PM literature in several ways. First, we estimate parameters using Bayesian methods, whereas most previous modelling (the exception being Strickland, 2017) has used optimisation methods like maximum likelihood. This allows us to obtain full probability distributions of likely values for each model parameter, rather than single point estimates. Second, in addition to model selection, we used posterior inference, in which conclusions are drawn based on comparisons of parameters posterior distributions (see Brooks & Gelman, 1998). The following sections briefly outline how the various theoretical accounts predict specific model parameters will behave under time pressure and PM demand, and how we will determine whether evidence for SAT effects, capacity-sharing, proactive, and reactive control is present in our data.

Time Pressure

Following the large literature on the speed-accuracy trade-off, we expect increased time pressure to be primarily reflected in decreased thresholds for both ongoing task and PM responses. That is, when there is less time available to make decisions, thresholds will be lowered in order to facilitate faster responding. In terms of the effects of time pressure on other model parameters, particularly accumulation rates, the evidence is mixed. Assuming time pressure decreases the quality of information processing, we would expect lower accumulation rates under high time pressure (Ho, Brown, van Maanen, Forstmann, Wagenmakers, & Serences, 2012). In contrast, assuming time pressure leads participants to become more aroused/engaged with the task and to invest greater effort, we would expect higher accumulation rates in high time pressure blocks compared to low time pressure blocks (Dambacher, Hubner, & Schlosser, 2011; Dambacher & Hubner, 2013; Hubner & Schlosser, 2010; Kleinsorge, 2001). These two effects are not mutually exclusive: one might occur, neither might occur, both might occur and cancel each other out, or both might occur with one having a stronger effect than the other. As such, we cannot unequivocably rule either out. Nevertheless, lower rates under time pressure would suggest a time-pressure related cost to processing efficiency regardless of increased effort, while higher rates under time pressure would suggest an increase in effort or arousal, regardless of processing costs.

Capacity-Sharing

PM capacity demand on the ongoing task would be reflected in decreased non-PM trial accumulation rates in PM blocks. As reviewed, this account has been rejected for at least eight previous data sets (Heathcote et al., 2015; Horn & Bayen, 2015; Strickland et al., 2017). However, given the novelty of our more complex and dynamic ATC task, and the fact that we are using a completely non-focal PM cue which would have a higher capacity requirement according to capacity-sharing theories (Einstein & McDaniel, 2005; Smith, Hunt, McVay, & McConnell, 2007), it is possible that we may find evidence of capacity sharing.

However, another possibility raised in recent work on mind-wandering in PM tasks (Rummel, Smeekens, & Kane, 2016; Kane & McVay, 2012; McVay & Kane, 2009; Smallwood, 2013; Smallwood & Schooler, 2015) is that the additional demands of the PM task reduce the frequency of task-unrelated thoughts, thereby increasing task focus during PM blocks. Assuming engaging in thoughts unrelated to the task at hand negatively affects the efficiency of information processing, we would expect increased ongoing task accumulation rates in on non-PM trials in PM blocks (in which less mind-wandering occurs) and lower ongoing task accumulation rates in control blocks (in which more mind-wandering occurs; Kane & McVay, 2012) - essentially the opposite effects to what would be predicted under capacity demand. As with the accumulation rate predictions related to time pressure, these possibilities are also not mutually exclusive. Lower rates under PM load would suggest capacity demands but not rule out increased effort or task focus, while higher rates under PM load would suggest increased effort or focus but not rule out capacity demands.

Proactive Control

Strategic delay and PMDC theories predict ongoing task thresholds will be proactively controlled in PM blocks in order to facilitate PM responding. In line with previous findings (Heathcote et al., 2015; Strickland et al., 2017), we expect that ongoing task thresholds will be higher in PM blocks compared to control blocks. Our design allows both ongoing task stimuli (conflicts and nonconflicts) to be PM targets, and PM cues are divided evenly between the two stimulus types. This is expected to lead to similar competition between the PM response and both ongoing task responses, and as such we expect to see similar threshold increases for both response types (conflict and nonconflict).

Reactive Control

A further prediction of PMDC is that that ongoing task accumulation rates can be reactively controlled (inhibited) on PM trials as compared with non-PM trials (Strickland, et al., 2017). Naturally, the PM accumulation rate should be higher on PM trials due to the processing of PM related stimulus attributes that are not present on non-PM trials. In addition however, rates for the ongoing task accumulators are expected to be lower on PM trials. This is because although both PM and non-PM trials contain equal evidence that a stimulus is a conflict or nonconflict, on PM trials the accumulators for the ongoing task responses may receive additional inhibitory input from the PM detector, thus reducing their rates of accumulation (Strickland, et al., 2017). As such, we expect ongoing task rates to be lower on PM trials, which will provide positive evidence that reactive control processes are present.