Decision Science: A New Hope

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Title: Decision science: A new hope.

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Abstract

Decision science is an area of enquiry that crosses many disciplines, from psychology to economics, each with their own perspective of decision making. Traditionally, mathematicians have envisaged decision making as a purely rational endeavour, whereas psychologists and behavioural economists have critiqued this narrative, and suggested that cognitive short cuts are the real mechanisms behind how decisions are made. However, contemporary dual process theorists argue that two systems of the mind exist: system one (intuitive decision making); and, system two (rational decision making). The current review will present a relatively new metaphor for decision making: the unified threshold model. This model is a global approach to decision making which allows both intuitive and rational decision making processes to be explained in a more flexible manner than the dual process model. This review will introduce the reader to different types of threshold models (Counter and Diffusion), their assumptions, and their ability to explain decision making behaviour. Implications and future research will also be discussed. In summary, the aim of this review is to highlight that the unified threshold model of decision making may be a more adequate explanation of decision making data in comparison to previous models and theories.

Keywords

Decision science, normative decision making, Bayesian theorem, heuristics and biases, unified threshold model, Diffusion Threshold Model.

Decision science: a new hope

A decision is a choice that an individual has to make between at least two alternatives; the decision maker may be motivated to obtain, or elude, a certain outcome (Glöckner & Betsch, 2012; Gold & Shadlen, 2007; Schall, 2005). Further, when faced with a choice, an individual will carry out a task and should be able to give some explanation for their decision (Schall, 2005). Although it may be clear to the layperson what a decision is, the ways in which individuals use different decision making strategies to reach certain outcomes, and how complex these strategies can be, is less clear. The current review will discuss decision making from a number of different perspectives including but not limited to: the normative approach, heuristics and biases and the dual process theory of decision making. By reviewing each of these approaches of decision making, it will become clear that these approaches are only able to explain decision making processes to a satisficing level. The current review aims to introduce readers to a relatively new type of model of decision making (i.e., unified threshold models) that aspires to be the new hope of decision science, and thus explain decision making behaviour more optimally. This unified threshold model of decision making shares with the dual process model its ability to explain both rational and non-rational judgments. However, the unified threshold approach to decision making is more flexible than the dual process model in that it perceives rationality and intuition to be poles at either end of a spectrum, with each mode of decision making only differing in regard to cue usage (Lee & Cummins, 2004). In addition, this review hopes to introduce the reader to different types of threshold model (i.e., the Diffusion Threshold model and Counter Threshold model), their respective assumptions and their abilities to explain decision making behaviour. Both practical and theoretical implications relating to the Diffusion Threshold Model (i.e., the model that best explains decision making behaviour) are also discussed. Furthermore, the authors hope to show that unified threshold models of decision making (Specifically Diffusion Threshold Models) may be decision science new hope.

The Bayesian Menace: an introduction to rational decision making.

Initially, philosophers, psychologists, mathematicians and economists viewed individuals as being highly rational and they treated the human mind as a "Laplacean Demon" (Gigerenzer & Goldstein, 1996, p.650). This means that limitations of the mind, such as limited capacity, cognitive overload and time restraints, were not taken into account (Gigerenzer & Goldstein, 1996). Humans were thought to have extraordinary decision making abilities, and used logic, rationality and probabilities to work out what was the most appropriate alternative to take in relation to a choice (Cornish & Clarke, 1986; Gigerenzer & Goldstein, 1996). Therefore, rational decision making can be defined as decision making processes that integrate all of the information available and that lead to outcomes with the most utility.

Many models use this rational method of decision making to establish how individuals come to reach decisions. One such model is the Bayesian model (Cummins, 2012; Gigerenzer, 2002; Kahan, 2015; Simon, 2004). This model is probabilistic, in that it works on the basis that the prior probability and conditional probability (which is based on evidence) allow a prediction or a decision to be made (Cummins, 2012; Gigerenzer, 2002; Kahan, 2015; Simon, 2004). This model also assumes that each piece of information is evaluated (i.e., given a probability) independently in a sequential and linear fashion until a judgment is finally reached using all of the available information (Cummins, 2012; Kahan, 2015; Lee & Cummins, 2004; Simon, 2004). The Bayesian model of decision making is a normative approach to decision making, and has been seen by some as the benchmark to use when investigating human decision processes (Cummins, 2012; Gigerenzer, 2002).

There are many criticisms of rational approaches to decision making, such as Bayesian models, however. One potential criticism of the Bayesian model is its complexity (Thagard, 2004), as the model analyses all the information available in particular scenarios, and this makes it unlikely that people will use this type of decision making strategy when analysing information. This is simply because of the cognitive costs and time limitations associated with such an in-depth analysis of the available information (Bröder & Schiffer, 2003). Consequently, Bayesian theorem may not mirror decision making processes that occur in real life (Pennington & Hastie, 1981). In addition, analysing all of the information available may make it unlikely that important information will be used when making a decision (see Gigerenzer & Goldsetin, 1996). If all of the information is processed, the significance of certain pieces of information may be lost; thus, the quality of information may be more important than the quantity used.

The rational choice theory is another normative theory of decision making. This theory of decision making assumes that decision makers are motivated by utility (Friedman, 1953). This theory was born out of philosophy and economics but has been extended to politics and criminology (Cornish & Clarke, 1986). Many theories fall under the banner of rational choice. One such theory is the subjective utility theory (Savage, 1954), this theory, like all rational choice theories, assumes that decision makers choose the outcome with the highest expected utility. For example, if choosing which car to buy with two possible options (e.g., car A vs. car B), the theory suggests that you will evaluate each factor (fuel consumption, price of car, millage) associated with the decision in relation to costs and benefits, this will then allow you to generate a total expected utility for each of the potential options, which will then form the basis for your decision (Becker, 2003). Tversky and Kahneman (1986) found, however, that decision makers do not always pick the option with the most utility, and will chose an option with lower net gain rather than risk a greater gain (i.e., they are risk averse); this deviates from what many rational choice models would predict. They also found that decision makers deviate from the invariance principle, which is a key principle of many rational choice models, as the description (or frame) of their decision tasks had an impact on the choice that was ultimately chosen.

Tversky and Kahneman's experiments on framing highlighted that normative models of decision making cannot fully explain decision making behaviour, and out of the ashes of rational choice theory prospect theory was born (i.e., decision makers do not always choose the outcome with the most utility; Tversky & Kahneman, 1986). A recent literature meta-analysis by Steiger and Kuhberger (2018) suggested that framing effects are real, and that experimentation on such effects has been reliable. The effects of framing have been found to have an impact on a number of different applied environments, from psychiatric risk assessments (Jefferies-Sewell, Sharma, Gale, Hawley, Georgiou, & Laws, 2015) to politics (Druckman, 2001). Furthermore, the framing effect shows that rational decision making models cannot always explain the decision processes of decision makers.

Framing effects can be attenuated, however, and are dependent on a number of factors (Druckman, 2001). Druckman (2001) showed that heterogeneous discussions in nonexperts (different participants receiving different frames of same decision) and homogeneous discussions in experts (different participants receiving same frames of same decision) attenuate framing effects. McElroy and Seta (2004) showed that framing effects only occurred when the right hemisphere of the brain was activated, whereas framing effects were not present when the left hemisphere was activated. Further, Thomas and Miller (2012) showed that prompts to think "like a scientist" promoted analytical decision making and reduced the framing effect (p. 143). These results highlight that the framing effect can be attenuated and that rational processing is possible, thus suggesting that neither rational choice models nor prospect theory explains decision making behaviour fully; this idea of decision makers being able to be both rational and nonrational will be discussed again in the section named: “The return of the rational mind”.

In summary, rational approaches of decision making can be seen to be unrealistic approaches to decision making that only explain part of the process. Individuals do not always make rational decisions, and Tversky and Kahneman’s (1991) seminal work on framing effects highlights this. Ironically, framing effects have also been shown to be ineffective at consistently explaining decision processes. Therefore, we will now turn to Tversky and Kahneman’s work on heuristics and biases, and will evaluate how effective said approach is when explaining decision making processes.

Attack of the heuristics: an introduction and evaluation to the heuristics and biases programme.

Tversky and Kahneman (1974, 1981) took a different approach to decision making; they accepted that normative models were ideal, but they believed that decision makers did not always follow normative models of decision making. Tversky and Kahneman revolutionised the field of decision science by suggesting that their new heuristics (cognitive short cuts) allowed decision makers to reach outcomes efficiently. A heuristic is a rule of thumb technique that allows individuals to make decisions without using heavy cognitive computation, thus easing cognitive load (Gigerenzer & Goldstein, 1996; Tversky & Kahneman, 1974, 1981). There are three ‘classic’ heuristics that were originally proposed by Tversky and Kahneman (1974, 1981): 1) *representativeness*; 2) *availability*; 3) and, *anchoring and adjustment*. These heuristics and their associated biases will now be briefly discussed.

The representativeness heuristic relates to people ignoring base rate information, and instead incorporating context and preconceived information when forming their judgments (Tversky & Kahneman, 1974, 1981). One reason for the representativeness heuristic being used by decision makers may relate to cognitive load (Tversky & Kahneman, 1974, 1981), as it is much easier (in terms of cognition) for individuals to base their judgments on stereotypes in comparison to base line statistics (Gigerenzer, 2002). However, the representativeness heuristic's ignorance of base line statistics can lead to many different types of cognitive biases and fallacies (decisions based on flawed logic according to normative models), such as the base rate fallacy (ignorance of the prior probability). The representative heuristic has been one of the most widely studied heuristics because of its association with stereotyping, racism and prejudice. For instance, Chan and Wang (2014) found that stereotyping has an impact on hiring outcomes, with females being more likely to be hired in female dominated careers, and males being more likely to be hired in male dominated careers.

The availability heuristic is another heuristic investigated by Tversky and Kahneman (1974). It works on the premise that individuals make decisions founded on how easy information comes to mind, allowing decisions to be made quickly and with relative ease (Tversky & Kahneman, 1974, 1981). However, this heuristic can cause people to overestimate the probability of an easily imagined event occurring (Tversky & Kahneman, 1974, 1981), which could bias people's judgments in a number of situations, including in relation to financial decisions. The availability heuristic can also cause decision makers to make errors in relation to both predicting the likelihood of an event occurring and when calculating the frequency of a reference group, and has been shown to bias the information that decision makers utilise (Tversky & Kahneman, 1973). For instance, Barber and Odean (2008) highlighted that when individuals are deciding on which stock to buy, they usually only think about the stock that they have recently been intrigued by.

A final classic heuristic, originally proposed by Tversky and Kahneman (1974, 1981), is the anchoring and adjustment heuristic. This heuristic suggests that people's judgments are sensitive to anchors (Tversky & Kahneman, 1974, 1981). Anchors are normally the first pieces of information given to decision makers, and they have a disproportionate effect on the decision making process and outcome. Tversky and Kahnman (1974, 1981) demonstrated that participants were sensitive to previously presented numbers, which caused an anchoring effect that was then adjusted for when making the final decision. However, these adjustments were often 'under-adjusted' and remained close to the original value (Tversky & Kahneman, 1974, 1981). Despite this heuristic first being studied over forty years ago, the anchoring and adjustment heuristic continues to be studied in disciplines relating to finance and civil law (Feldman, Schurr, & Teichman, 2016; Siddiqi, 2016). For instance, Siddiqi (2016) suggested that the "volatility of the underlying stock returns" are used as an initial anchor by decision makers on the stock market, these decision makers then adjust upwards, although insufficiently, to reach a call option volatility (p.32).

Many of Tversky and Kahneman's (1974, 1981) heuristics are beneficial on more occasions than they are incorrect, however. Researchers such as Lieder, Griffiths, Huys, and Goodman (2017) have shown that the anchoring and adjustment heuristic does not symbolise an irrational method of decision making, and rather proposes that the adjustment from initial anchors is a rational behaviour, with the amount of adjustment being dependent on the importance of the decision. Further, Lieder et al. (2007) suggest that decision makers calculate time and error costs when estimating how much adjustment from the anchor is necessary.

In addition, it has been shown that decision making based upon heuristics can lead to accurate outcomes being reached (Klein, 2001). For example, Gigerenzer and Goldstein (1996) have found that fast and frugal heuristics, such as the Take The Best (TTB) heuristic (i.e., where a decision is made based upon the first cue that allowed two outcomes to be discriminated), are more efficient at making predictions than mathematical methods, such as multiple regressions. This, therefore, proposes that heuristics may direct decision makers to accurate inferences, and that prejudices may be an integral part of the decision making process (Gigerenzer, & Brighton, 2009; Gigerenzer & Goldstein, 1996; Snook & Cullen, 2008). Furthermore, the research on heuristics and biases highlights that sometimes heuristics are beneficial, and that other times heuristics lead to errors. This suggests that animals who evolved only a rational manner of decision making (absent of bias) would be disadvantaged in some contexts, and that animals who only reasoned intuitively would be disadvantaged in others. Therefore, it is suggested that Homo sapiens would have greatly benefited from having two separate methods of making decisions: 1) intuitive and 2) analytical (Kahneman, 2011). This is because an intuitive method of decision making saves cognitive load when decisions are routine and effortless (Shah & Oppenheimer, 2008), whereas an analytical system generates logic and reasoning when a decision is effortful and irregular, thus suggesting a model of decision making that encompasses both rationality and nonrationality may be more realistic.

Contemporary research has also highlighted that heuristics can be attenuated and that analytical decision processes can be promoted. For instance, research has shown that experience and expertise attenuates biased decision processes (Chan & Wang, 2014), and that motivation can attenuate the decision maker from using heuristics (Zhang, Zhao, Cheung, & Lee, 2014). Therefore, an individual may make some decisions rationally (if motivated), and may use heuristics (if not motivated) for other decisions. Neither the normative approach nor the heuristics and biases approach of decision making gives a full explanation of how individuals make decisions, for that a unified model of decision making is needed.

The return of the rational mind: A dual process theory of decision making.

Modern decision science has almost come full circle, as rationality and intuition have now been incorporated together into Kahneman's (2011) dual process theory. In this theory, Kahneman suggests that individuals possess two separate parts of the mind that govern how a decision is made: system one and system two (sometimes referred to as type one and type two; Evans & Stanovich, 2013). System one is an evolutionary old part of the mind that is utilised by a number of animals (including humans), it is intuitive and utilises heuristics to make efficient decisions (Evans, 2003). Although, system one is not merely one system, it is a multifactorial system that is made up of a plethora of cognitive short cuts that allow decision makers to make intuitive responses (Evans & Stanovich, 2013). System two on the other hand is more rational, conscious and effortful, and it evolved relatively recently in human history; around 50,000 bc (Evans, 2003). There is support for the Dual Process theory as DeNeys (2006) found that correct decisions on a conjunction fallacy task take longer than incorrect decisions, which fits with Kahneman's (2011) description of system two as said system is thought to be more deliberative and effortful than its intuitive counterpart. Research from neuroscience does suggest that specific brain areas are associated with rational (orbital and medial pre-frontal cortex) and biased (amygdala) decision making (De Martino, 2006), providing further evidence for the existence of these two systems.

Further, Phillips, Fletcher, Marks and Hine (2016) found in a meta-analysis that intuitive decision strategies shared a positive relationship with experience, but had a negative association with the normative correct response (i.e., performance). They also discovered that rational decision making (or reflective thinking styles) was positively associated with performance and experience. In addition, Phillips et al. (2016) showed that time pressures decreased the relationship between rational decision making and performance, the same was not true for the relationship between intuitive decision making and performance. The strongest relationship between rational decision making and performance was found to be between either the ages of 12 to 18 or for individuals that were 25 and plus, which highlighted that age is an important mediator between the mode of decision making and performance. Furthermore, Phillips et al.'s (2016) meta-analysis showed that a model that incorporates both rational and intuitive processes of decision making is necessary to account for individual differences and for the effects that context has on decision making performance.

Despite the appeal of the dual process theory of decision making, it has been criticised for being too simplistic as some decisions cannot be categorised within either of the two systems, and may fall in a middle zone of quasi-rationality (Cader, Campbell, & Watson, 2005; Dhami & Thomson, 2012; Hammond, 1996). Keren and Schul (2009) go as far to propose that there is a lack of scientific evidence supporting two systems of the mind, as decision making attributes (e.g., conscious vs. unconscious; emotional vs. analytical) do not cluster together to form a dual process model. Evans and Stanovich (2013), however, counter the continuum vs. discrete type debate by suggesting that individual differences exist with the type two system (rational system), and that a continuum exists within this system. Nevertheless, is a dual process theory of decision making needed if a unified decision making theory can account for the data? Kruglanski and Gigerenzer (2011) argue no, they propose that a unified model of decision making is satisficing enough to explain decision making data.

One example of a unified theory of decision making is the Cognitive Continuum Theory, and this theory suggests that rationality is on a continuum, with intuitive and rational decision making at either ends of this continuum and quasi-rational decision processes being somewhere in the middle (Cader et al., 2005; Dhami & Thomson, 2012; Hammond, 1996). This theory is a lot more malleable than the dual process theory of decision making, as it explains rational and intuitive behaviour in a more flexible manner. Nevertheless, the Cognitive Continuum Theory fails to account for the metacognitive processes behind why some individuals display rational behaviour and why others make intuitive decisions. Further, the Cognitive Continuum Theory lacks utility into how individuals actually make everyday decisions, as it cannot explain the process behind how a decision is reached.

Unified threshold models of decision making, however, may be able to explain the mode of cognition a decision maker utilises when choosing an outcome. A number of pieces of research have proposed that thresholds that vary in regard to cue usage can explain both rational and intuitive judgements (Curley, Murray, MacLean, & Laybourn, 2017; Curley, MacLean, Murray, Pollock, & Laybourn, in press; Curley, Murray, MacLean, Laybourn, & Brown, in press; Lee & Cummins, 2004; Ratcliff & Smith, 2004). In other words, thresholds that are reached using a satisficing amount of information mirror intuitive judgements, and thresholds that are reached using an optimal amount of information mirror rational decision processes. This, therefore, suggests that unified threshold models may be a better metaphor to use when describing decision making behaviour, as said models can explain both intuitive and rational decision processes, whilst also explaining the metacognitive processes behind the cognitive mode of the decision maker.

Decision Science: A new hope.

The remainder of the current review will discuss how a unified threshold model of decision making can explain both rational and intuitive decision processes. A unified threshold model aims to encompass all of the heuristics within the fast and frugal research paradigm. That is, instead of a number of heuristics being used to make decisions in different environments, one decision making strategy that fits all environments, through varying cue utilisation, is argued to exist (Lee & Cummins, 2004). In the threshold model, it is argued that decisions are made when a specific threshold is met (Ratcliff & Smith, 2004) and that said threshold might shift to suit different environments (Lee & Cummins, 2004). If intuitive decision making is needed, the threshold is low, meaning fewer cues are used, whereas if rational decision making is needed, cue utilisation will increase as the threshold increases.

One of the main reasons for the emergence of a threshold model of decision making was because participants have been shown to use both non-compensatory and compensatory processes when making decisions in experiments (Lee & Cummins, 2004); hence, existing models were not able to describe decision processes fully. Previous research has shown that different decision making strategies, including the TTB approach, are used in some scenarios and not in others (Bröder & Schiffer, 2003; Brown & Tan, 2011; Hoffmann, von Helversen, & Rieskamp, 2013; Sojka & Giese, 2001). For instance, verbal information and memory-based tasks are likely to cause participants to use strategies associated with the TTB approach, and rational processes of decision making are more associated with visual, image based tasks and tasks that do not rely on memory (Bröder & Schiffer, 2003; Bröder & Gaissmaier, 2007; Newell, Weston, & Shanks, 2003). Therefore, a unified threshold model may give a more comprehensive account of decision making across different scenarios in comparison to other theories/models of decision making (Newell & Lee, 2010).

Threshold models may give a more global explanation of decision making than heuristic models can, as threshold models can explain everything from the TTB model to rational decision making, without adding additional conceptions of complicated strategies (Lee & Cummins, 2004; Lee et al., 2014). They can also explain Tversky and Kahneman's (1974) heuristics through having a satisficing and biased threshold, biased in that the threshold may favour a particular outcome. Furthermore, the threshold model encompasses more data, thus making said model more complete in regard to the scientific goal of generating global theories, which are of commonplace in the natural sciences.

The unified model of decision making has also been described as an "adjustable spanner" (Newell, 2005, p.7). Essentially, rather than changing strategies (or heuristics) to suit different environments, decision makers simply tailor their thresholds, and make decisions once a threshold has been reached (Newell, Collins, & Lee, 2007; Newell & Lee, 2010). That is, decision makers adjust their tolerance for how much evidence is acceptable to make a decision, and these tolerance levels/thresholds can change depending on the situation (Lee & Cummins, 2004; Newell & Lee, 2010; Söllner, Bröder, Glöckner, & Betsch, 2014). Consequently, in some environments (e.g., what university to go to) people may use all of the information supplied, whereas in less important decisions (e.g., what to wear to go to the pub) individuals may only have a low threshold, allowing the decision to be made using less cues (Newell & Bröder, 2008; Söllner et al., 2014).

The Evidence Accumulation Model (i.e., a type of threshold model; Lee & Cummins, 2004) uses elements of the TTB algorithm and the rational decision making approach (Bergert & Nosofsky, 2007); these elements essentially relate to threshold level (Newell & Bröder, 2008). For instance, if the threshold for a certain decision is small, then individuals may be frugal in their use of cues and thus mirror the TTB heuristic (Lee et al., 2014; Newell & Bröder, 2008). However, if individuals are using many cues, or all of the cues to make a decision, and demonstrating rational behaviour then it might be because their threshold for this particular decision is relatively high (Lee et al., 2014; Newell & Bröder, 2008).

Lee and Cummins (2004) tested the Evidence Accumulation Model by comparing the usage of two different models of decision making with said model. One of the models that was used was the rational model (i.e., RAT; Lee & Cummins, 2004). In this model, individuals use all the information and will chose the outcome with the most support. The other model used in this research was the TTB approach, which was discussed earlier. The only difference between these two models relates to accumulation of evidence (Bergert & Nosofsky, 2007; Lee & Cummins, 2004; Newell & Lee, 2009). When the TTB approach was used, individuals accumulated less evidence, and thus had a lower threshold (Bergert & Nosofsky, 2007; Lee & Cummins, 2004). In contrast, when the RAT strategy was chosen, individuals accumulated more, or all, of the information/cues, which means that they had a higher threshold (Bergert & Nosofsky, 2007; Lee & Cummins, 2004).

Lee and Cummins' (2004) comparison of the RAT and TTB models found that over 52.5% of the participants that neither of the two strategies were used exclusively. Nevertheless, a unified threshold model of decision making that fused the RAT and TTB model could account for more of the observed data than either of the other two models could do on their own: unified threshold model = 85.5%; RAT model = 64%; and, TTB model = 36% (Lee & Cummins, 2004). Further, Dieckmann & Rieskampm (2007) showed that in environments where there was a lot of useless information provided, the TTB option was optimal to a naïve Bayes strategy, whereas in other contexts, where not a lot of redundant information was provided, the naïve Bayes strategy was optimal. This once again highlights that a threshold that varies in regard to information usage allows a decision maker to be more adaptable to new decision making contexts. In summary, the unified threshold approach to decision making may be a new alternative that may help to explain decision making behaviour more fully than previous approaches to decision making. Nevertheless, a plethora of different threshold models exist, the next section of this review will evaluate based on previous research which threshold model of decision making has the greatest utility to decision science.

Threshold models awaken: a comparison and evaluation of different Threshold models of decision making.

Various unified threshold models exist, and each of these models can be split across two categories of unified threshold model: Counter Threshold Models and Diffusion Threshold Models (Ratcliff & Smith, 2004). One similarity across the two separate types of threshold model is that both of them have thresholds that can vary in regard to cue usage, with frugal cue usage mirroring intuitive processes and compensatory cue usage mirroring rational processes. However, there are a number of ways in that these two separate categories of threshold model differ from one another. These differences will be explored further in the remainder of the current section through discussing the respective assumptions of both Counter Threshold Models and Diffusion Threshold Models.

Counter Threshold Models suggest that when a decision is being made, each outcome of the choice is represented by a counter, and evidence is evaluated in a binary manner in respect to what outcome it favours (Ratcliff & Smith, 2004). When evidence favours a particular outcome, it is placed in the outcomes respective counter, and this occurs until the evidence allows an outcome to be favoured (i.e., when evidence that supports a particular outcome allows a threshold to be reached). Therefore, Counter threshold models assume that decision makers collect information in separate counters that represent the outcomes of a choice, and that once enough information has been collected for an outcome to be favoured, then that outcome is chosen. Counter Threshold Models have absolute stopping rules, and once a threshold is reached, information search terminates (Ratcliff & Smith, 2004).

This absolute stopping rule approach to decision making can be broken down further into two different types of Counter Threshold Model. First, there is the Accumulator Model where evidence intake varies but occurs at fixed intervals (Ratcliff & Smith, 2004). Second, there is the Poisson Counter Model (Lemieux, 2007) where evidence accumulation is fixed, but the accrual of information happens at variable times across a continuous time scale (Ratcliff & Smith, 2004). These two models are the most relevant within the current review as they are the main successors of early Counter Threshold Models, they are well cited within the literature and they vary enough to give a full view of what can be encompassed within a Counter Threshold Model of decision making (Ratcliff & Smith, 2004).

In the Accumulator Model, evidence is collected across two separate counters (Ratcliff & Smith, 2004; Smith & Ratcliff, 2004). Varying evidence amounts are collected in a sequential fashion, using a sensory referent mechanism, at discrete time periods (Ratcliff & Smith, 2004; Smith & Ratcliff, 2004; Van Maanen & Van Rijn, 2007). The sensory referent mechanism allows information to be placed into the appropriate counters (one or two), each of which representing a different outcome, and weighted. If information surpasses the sensory referent, which is equivalent to zero, the residual difference between the information collected and the sensory referent is placed into counter one (Ratcliff & Smith, 2004). However, if the information falls short of the sensory referent, the residual difference between the information collected and the sensory referent is placed into counter two. The information is collected in separate counters until one threshold is reached (Ratcliff & Smith, 2004; Smith & Ratcliff, 2004); this then allows a decision to be made. Models that are related to the Accumulator Model (e.g., the selfregulating accumulator) have also been used to map how confidence can change and adapt thresholds (Hausmann & Läge, 2008;

Lee & Dry, 2006; Lee, Newell, & Vandekerckhove, 2014), highlighting how effective unified threshold models are at explaining decision data.

Conversely, the Poisson Counter Model proposes that information is independently accrued in exact pieces (i.e., a cue or a value) at a constant rate (continuously distributed times), and is gathered on separate counters representing different outcomes (Lemieux, 2007; Merkle & Van Zandt, 2006). The evidence continues to accrue until a threshold is reached (Smith & Ratcliff, 2004), which then allows a decision to be made. Further, the quality of the information can increase the accumulation of one count over another (Ratcliff & Smith, 2004). This links to naturalistic decision making, as the environment also has an effect on the decision making process (Gigerenzer & Goldstein, 1996).

In contrast to Counter Threshold Models, Diffusion Threshold Models suggest that when making a decision, individuals integrate information until they reach a point (or threshold) where one outcome is favoured relative to the opposing outcome. In Diffusion Threshold Models, information that pushes the decision maker away from one threshold attracts the decision maker to the opposing threshold (Ratcliff & Smith, 2004). This is because thresholds exist on the same continuum, rather than on separate counters, in Diffusion Threshold Models. Two separate Diffusion Threshold Models exist: the Wiener Diffusion Model; and the Ornstein-Uhlenbeck Diffusion model (Ratcliff & Smith, 2004).

The Wiener Diffusion Model, which was named after the mathematician Norbert Wiener who discussed stochastic processes (Smith & Ratcliff, 2004). Smith and Ratcliff (2004) were the first researchers to describe the model within a psychological context. In this model, information is collected from a starting point (**Ș**), and is gathered until one of two thresholds are reached (e.g., Threshold **A** and Threshold **B**; Ratcliff & Smith, 2004; Smith

& Ratcliff, 2004). Once a threshold is reached, a decision is made (Smith & Ratcliff, 2004). The rate of the accumulation of information from the starting point, **Ș**, to either of the thresholds, **A** or **B**, is called the drift rate (**Θ**) (Ratcliff & Smith, 2004).

The drift rate is the mean information accrual from a stimulus over specific time units (Ratcliff & Smith, 2004). Drift rates are relatively flexible as they can change depending on the complexity of the decision making task (Ratcliff & Smith, 2004). For example, drift rates are larger for simple decisions and are smaller for decisions that are more complex. This has implications for real world decisions, as decisions with small drift rates involving low information quality will have longer response times, and may be more likely to be incorrect (Ratcliff & Smith, 2004; Smith & Ratcliff, 2004). Drift rates can be positive or negative depending on whether the information that has been accumulated is causing individuals drift to move towards a negative threshold or a positive threshold (Ratcliff & Smith, 2004).

An additional important theoretical contribution of the Wiener Diffusion Model is that the starting point of the model can change (Ratcliff & Smith, 2004). Individuals may not start off symmetrically, in-between the two thresholds, but may instead be biased towards a certain threshold (Ratcliff & Smith, 2004). This model may, consequently, explain decision biases (Ratcliff & Smith, 2004; Smith & Ratcliff, 2004) that were originally identified by Tversky and Kahneman (1974, 1981), as discussed earlier.

A skewed starting point (closer to one threshold relative to another) has also been associated with quicker decisions that are less accurate (Ratcliff & Smith, 2004), once again mirroring heuristic processing. If a starting/prior point is close to a threshold, then less information is needed to reach said threshold, which increases the likelihood of an error and makes the decision more likely to be quick (Ratcliff & Smith, 2004), thus skewed starting points may facilitate fast and frugal decision making. The Wiener Diffusion Model can also explain commonly observed psychological phenomena, such as the speed/accuracy trade-off (Franks, Dornhaus, Fitzsimmons, & Stevens, 2003; Smith & Ratcliff, 2004). In addition, through allowing drift rate and starting points to vary, the model can explain why errors happen quickly in accuracy focused tasks and why errors happen more slowly in speed focussed tasks (Ratcliff & Smith, 2004). Furthermore, the Diffusion Threshold Model may help to explain why previous research has found conflicting evidence in relation to heuristic accuracy rates.

Previous research has suggested that incorrect decisions occur when decision makers deviate from the classical rational approach (Tversky & Kahneman, 1974, 1981). Nevertheless, the Wiener Diffusion Model proposes that errors and correct responses come from fluctuations and variability in starting points, drift rates, threshold levels and noise (Ratcliff & Smith, 2004; Smith & Ratcliff, 2004). In summary, the Wiener Diffusion Model incorporates mathematical principles from a normative approach, and has inbuilt biases attached within it, thus allowing it to be a descriptive mathematic model that is able to describe decision making data to an optimal standard. The second Diffusion model that will be mentioned here is the Ornstein-Uhlenbeck model (as described by Ratcliff & Smith, 2004). This model is essentially an extension of the Wiener Diffusion Model of decision making, and the only difference is that this model proposes that the more evidence that is collected, the more decay will happen; and decay is defined as a mathematical function that decreases the drift (Ratcliff & Smith, 2004). Psychologically, decay is equivalent to forgetting previous information as novel information is being processed.

Ratcliff and Smith (2004) conducted three separate psychophysics experiments and then tested the abilities of the four models mentioned above (The Accumulator Model; The

Poisson Counter Model; The Wiener Diffusion Model; and, the Ornstein-Uhlenbeck model) in relation to how well they explained their decision making data. The first study was a signal detection experiment, where participants were asked to make a judgment on whether the distance between dots was small or large. In experiment two, participants were asked to make a decision on whether a letter string was a word or a non-word. For the first two experiments, participants were told to either value accuracy or speed, and this value varied between the blocks of trials. In the final experiment, participants were asked to state whether they recognised or did not recognise a target word in relation to a previously shown list of words. As previously stated, each of the models were then fitted against the data (i.e., response times for correct and incorrect responses, accuracy rates and data distributions) from all three experiments. It was found that in the decision tasks that the Accumulator Model outperformed the Poisson Counter Model in relation to describing the decision making data. In addition, the decay function of the Ornstein-Uhlenbeck model was found to have an influence on how well the model fitted decision making data (Ratcliff & Smith, 2004). When the model had a moderate or large decay, it was found not to fit decision making data as well as the original Wiener Diffusion Model (Ratcliff & Smith, 2004). The Ornstein-Uhlenbeck model fitted Ratcliff and Smith's (2004) experimental data best when the decay parameter was zero (i.e., when it mirrored the Wiener Diffusion Model). Furthermore, over the thee experiments, Ratcliff and Smith (2004) found that the Wiener Diffusion Model fitted the decision making data the best when compared to the other three models.

In addition, a recent paper by Curley et al. (in press) found that decision making data was best explained by Diffusion Threshold Models in comparison to Counter Threshold models. Therefore, future research should utilise the Diffusion Threshold Model when investigating decision making behaviour, and should also test the efficacy of said model in applied environments. The next section will further explore potential avenues of future research and will discuss the implications that unified threshold models have for both theory and practice.

Implications and future research

Unified threshold models of decision making have the impact to lead to a paradigm shift in decision science, as the theoretical implications of said models are great. The first implication of unified threshold model is that it allows the importance of a decision to be captured (Lee & Cummins, 2004). Currently, decisions are viewed in a binary sense, they are either important and decision makers use rational processes to tackle them or they are trivial and decision makers use heuristics to make the decision. Not every decision is like this though; there is a gradient of importance related to decisions, and rationality can be viewed on a spectrum. Your decision of what to wear today is less important than your decision of what car to buy, which is once again less important than what job you decide to apply for (Lee & Cummins, 2004); and, different levels of rationality would be required to make each of the above decisions. The unified threshold metaphor of decision making is more dynamic than previous models of decision making (i.e., the dual process theory), however. Decisions can be viewed from every level of importance, with different levels of rationality associated with differing levels of task importance. Differences in the rationality and importance of the decision can then be reflected in unified threshold models by measuring how much information is needed to reach a decision threshold. In addition to this, and in relation to bounded rationality, the unified threshold model highlights to researchers and practitioners how much available information was provided by the environment and how strong said information was perceived to be (Lee & Cummins, 2004). When a lot of strong information is provided, decisions may be made quickly; whereas, slow decisions may mirror when the information presented was limited (Ratcliff & Smith, 2004).

In a practical sense, unified threshed models allow biases to be measured in a way that does not compare humans to normative models of decision making and rather compares biases to other people. Biases are seen to be deviations from the norm (Tversky & Kahneman, 1974), and by measuring how much information decision makers use to reach a threshold, decision scientists can measure how much individuals differ from one another in relation to compensatory decision making, thus highlighting when biases emerge (Curley et al., in press). For instance, Curley et al. (in press), in a juror decision making experiment, measured how many cues it took for individuals to reach their threshold, participants were then categorised across the verdicts they gave (Guilty, Not Guilty, and the Scottish specific acquittal verdict of Not Proven). They found that jurors who gave a Guilty verdict used significantly less information than jurors who gave either of the acquittal verdicts, thus highlighting that jurors who gave a Guilty verdict had a satisficing Guilty threshold, and were more biased to said threshold in comparison to the other jurors. This same methodology could be used to measure biases in other applied setting such as medicine. For example, do some doctors need less information to recommend surgery than others do because of a pre-consultation bias, or are some stock brokers biased towards a certain stock because of environmental pressures, and do they need less information to reach the threshold associated with this stock when compared to other stock brokers that make decisions within a different context. The use of the unified threshold metaphor is useful to practitioners because if it is known that certain types of people or certain circumstances cause thresholds to be reached frugally, and a frugal threshold is not optimal in that circumstance, then attempts can be made to evaluate the types of variables that promote more compensatory threshold. To do this previous research can be utilised which aims to attenuate biases (see Thomas & Miller, 2012).

Unified threshold models of decision making share elements with the Cognitive Continuum Theory in that unified threshold models propose that rationality is on a continuum which begins with intuitive processes. However, unified threshold models hold more utility in that they can be used to explain how decisions are actually made. Previously, decision science has had two separate types of literature on decision making.

The first type related to overarching theories, like the dual process theory and the Cognitive Continuum Theory, that highlight that decision making is made up of both rational and intuitive processes, but cannot really explain the process of how specific decisions are made. For example, the dual process theory highlights that a doctor who is deciding on the best course of action may under time pressures may use system one, and may use system two when they have more time to reflect. Nevertheless, the dual process theory does not explain the mechanics behind how the doctor chose which avenue to take. The second type relates to models that explain how decisions are reached, these are normally heuristic models, such as TTB model, that shows the process behind how a decision is reached. These models, however, are very specific and do not explain the majority of decision making behaviour (Lee & Cummins, 2004). Unified threshold models, such as the Diffusion Threshold Model, bridge the gap between these two separate types of literature on decision making models, however. For instance, unified threshold models show that decisions are made when information integration allows a threshold to be reached (Rarcliff & Smith, 2004), and thus explain the individual decision processes of decision makers; in a similar manner to the TTB heuristic. Second, they also explain the mode of cognition through measuring how compensatory the threshold was in order for it to be reached (Curley et al., in press), and consequently highlight how rational the decision maker was being, in a similar vain to the Cognitive Continuum Theory.

In addition, unified threshold models combine terms that are normally specific to different approaches within the discipline of decision science. For instance, information integration is normally associated with normative models of decision making, such as Bayesian models, whereas satisficing (using a limited amount of information) is more associated with heuristic processing and bounded rationality. However, the Diffusion threshold Model combines these terms, as decision makers can integrate a satisficing amount of information to reach a threshold (Curley et al., in press; Lee & Cummins, 2004; Ratcliff & Smith, 2004). Unified threshold models of decision making break decision science from the shackles of different disciplines, thus allowing researchers to have a more flexible and dynamic approach to the study of decision making. Nevertheless, only a limited amount of research has been conducted on threshold decision making, and more research is therefore needed.

Research traditionally investigating Diffusion Threshold Models (i.e., perceptual decision making tasks) has used visual and visuomotor tasks involving 'dots' on a screen within their experiments and asked participants if these 'dots' move to the right or the left (Bitzer, Park, Blankenburg, & Kiebel, 2014). Therefore, future research should investigate the Diffusion Threshold Models ability to describe decision processes in realistic environments (e.g., legal, medicine and finance). Despite the unified threshold models' strengths over other models, information is lacking in regard to how individuals choose a threshold. For example, why do some individuals select a satisficing threshold that mirrors heuristic processing? And, why do other people select a more compensatory threshold that mirrors rational processing? Therefore, future research should investigate the factors (e.g., individual differences and information available in the environment; Salas, Martin, & Flin, 2017) that may influence how a threshold is set. In addition, future research should investigate where satisficing thresholds are useful, and where thresholds that are more compensatory are needed. In a similar vein, researchers should enquire if more compensatory thresholds can be promoted through: the endorsement of analytical thought; increasing the motivation of the decision maker; and, expertise (Chan & Wang, 2014; Thomas & Miller, 2012; Zhang et al., 2014). Finally, future research may want to compare which model/theory of decision making (i.e., the dual process theory vs. the Wiener Diffusion Model) most adequately explains decision making data. As far as this researcher is aware no such research has been conducted, and a direct comparison of the two models is needed.

Conclusion

In conclusion, unified threshold models (specifically the Wiener Diffusion Model) of decision making may be decision sciences new hope at being able to explain decision making behaviour more optimally. Old hopes relating to normative decision making approaches and the heuristics and biases approach only explain some of decision making data. Both of these approaches cannot explain why sometimes it is beneficial to be intuitive, whereas on other occasions it may be more advantageous to use rational decision making processes. Kahneman's (2011) dual process theory did try to explain decision making data more adequately by encompassing separate systems of the mind for intuitive and rational processes. Although very influential, this theory is simplistic in its categorisation. In contrast, the unified threshold model of decision making gives a more flexible explanation of how the mind encompasses both rational and intuitive systems. Further, a dual process theory is not needed when a unified model can explain decision making data to an equal standard. Future research that compares the efficacy of the unified threshold approach with the dual process approach is needed, however. Only then will we know if unified threshold models (such as the Wiener Diffusion Model) of decision making are decision science's new hope, as previous literature seems to suggest, or if they are merely a good contender.

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