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Quantum Cognition: A New Theoretical Approach To Psychology

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Abstract

1 What kind of probability theory best describes the way humans make judgments under
2 uncertainty and decisions under conflict? Although rational models of cognition have become
3 prominent and achieved much success, they adhere to the laws of classical probability theory
4 despite the fact that human reasoning does not always conform to these laws. For this reason, we
5 have seen the recent emergence of models based on an alternative probabilistic framework drawn
6 from quantum theory. These quantum models show promise in addressing cognitive phenomena
7 that have proven recalcitrant to modeling by means of classical probability theory. This review
8 compares and contrasts probabilistic models based on Bayesian or classical vs. quantum
9 principles, and highlights the advantages and disadvantages of each approach.

10

11 **A new approach to cognitive science**

12 Cognitive scientists have long struggled to form a comprehensive understanding of how
13 humans make judgments and decisions under conflict and uncertainty. Decades of research have
14 seen two approaches crystalize to the surface—"heuristic" and "rational." The heuristic approach
15 is firmly rooted in Herbert Simon's notion of bounded rationality [1]. This approach posits that,
16 to make judgments and decisions, people tend to employ simple heuristics (e.g.,
17 representativeness, anchoring-and-adjustment, take-the-best), which may not always seem
18 rational. This can be viewed as a "bottom up" inductive process in the sense that humans learn
19 simple *ad hoc* rules that can be effective or not depending on the environmental conditions [2-4].
20 In stark contrast, the rational approach is founded on theories of subjective probability and
21 expected utility [5]. This approach posits that people can derive inferences from the Bayes rule
22 and decisions from the expected utility rule in a rational manner. This can be viewed as a "top
23 down" deductive process, wherein the same basic axioms can be used to derive inferences and

1 utilities across all environmental conditions [6, 7]. Recently, a third approach, called “quantum
2 cognition,” has emerged [8-10]. In common with the heuristic approach, it assumes that the
3 human decision maker is subject to bounded rationality. Moreover, like the rational approach,
4 inferences used for decisions are derived from basic axioms that define a probability theory.
5 However, the axioms are different from those employed by the Bayesian approach, and
6 consequently, so are the inferences that are derived from it.

7 To what probability theory does quantum cognition subscribe? This question may come
8 as a surprise to some readers, since by and large, cognitive scientists have been exposed to a
9 single probability theory—what we will call classical (more technically, Kolmogorov)
10 probability theory, on which Bayesian models rest. There are, however, several viable
11 probability theories upon which to build probabilistic models of cognition [11]. Quantum
12 cognition is one such alternative that is increasingly gaining attention [8-10]. What makes
13 quantum cognition controversial is that its associated probability theory was developed within
14 the field of quantum physics. This immediately raises skepticism: How could a probability
15 theory governing the behavior of subatomic phenomena have anything meaningful to say about
16 cognitive phenomena, such as decision making? Indeed, why even consider an alternative to
17 classical probability theory? How do the classical and quantum probability theories differ, what
18 critical assumptions do they make, and how can we decide which theory is superior for modeling
19 cognitive phenomena? This review will be guided by such questions. First, we present some
20 compelling psychological reasons why certain abstract principles in quantum theory are relevant
21 to cognitive phenomena. With this foundation in place, we will then briefly but systematically
22 compare the assumptions underlying classical and quantum probability theories. This
23 comparison provides the intuition regarding how each theory makes different predictions, and

1 how their prescriptions of what is rational differ. Finally, the conclusion summarizes the critical
2 differences between quantum and classical models, and identifies the reasons why they differ in
3 this way.

4 **From quantum physics to quantum cognition**

5 Less than 20 years ago, a group of scientists pioneered the bold idea of applying the
6 abstract principles from quantum theory outside of physics into the field of human cognition [12-
7 15]. They did not proceed from the assumption that there is something quantum-like going on in
8 the brain, but instead drew inspiration from both the mathematical structure of quantum theory
9 and its associated dynamic principles.

10 It was the mathematician John von Neumann [16] who axiomatized quantum theory in
11 the 1930's. Regarding these axioms, he stated, "The set theoretical situation of logics is replaced
12 by the machinery of projective geometry, which in itself is quite simple." ([17], p.244) He was
13 referring to the fact that the logic underlying classical probability theory is prescribed by
14 Boolean algebra, because of its set-theoretic foundation. The associated Boolean logic implies
15 that events can always be combined (e.g., via logical conjunction). The consequence, however, is
16 that logical conjunction is commutative, so expressing the combined event "*A and B*" is the same
17 as stating "*B and A*." In other words, the order of the events does not matter. In contrast, inherent
18 in von Neumann's "machinery of projective geometry" is non-commutativity: The sequence of
19 events "*A and B*" is not necessarily the same as the sequence of "*B and A*."

20 To illustrate the idea of commutativity, consider an example of public opinion polls.
21 Polling companies know well that asking respondents to judge the trustworthiness of a politician
22 A followed by another politician B can generate different results compared to when the
23 politicians are judged in the reverse order [18-19]. This example highlights the fact that human

1 judgment is not necessarily commutative. To account for this non-commutativity, a classical
2 model needs to include the sequence of evaluations as part of the description of the event (e.g.,
3 “*A and B*” and “*A before B*”). This point will be taken up in more detail later. Meanwhile, we
4 can begin to appreciate why the mathematical structure of quantum theory might lend itself to
5 the modeling of human cognition as many cognitive phenomena crucially depend on the
6 sequence or order of the cognitive processes and measurements (e.g., judgments and decisions),
7 and quantum theory was initially developed to address order effects of measurements in physics.
8 Of course, not all judgments and decisions are sensitive to order. For example, if one decision is
9 whether to drive a car to work or take a bus, and the other is whether to have a dog or cat as a
10 family pet, then we typically would not expect the outcomes of these decisions to be sensitive to
11 the sequence in which the decisions are taken. In principle, these decisions can be evaluated
12 simultaneously and evaluating one does not interfere with what we think about the other, so the
13 same outcomes are produced regardless of the order of decisions.

14 The preceding two examples provide a simple introduction to the principle of
15 complementarity ([20], see Glossary). When this principle is transmigrated into quantum models
16 of cognition, it states that we need to distinguish between two kinds of events, compatible and
17 incompatible, in order to understand how humans reason under uncertainty. More specifically,
18 two events (e.g., two questions), *A and B*, are deemed “compatible” if they can be considered
19 simultaneously. That is, the order in which they are considered does not matter to the finally
20 observed or measured values. Conversely, events *A and B* are defined as “incompatible” if they
21 cannot be considered simultaneously but thus have to be taken sequentially. In this case the order
22 does matter to the finally observed or measured values. The complementarity principle
23 essentially posits the existence, or even the prevalence, of incompatible measures. As a note in

1 passing, Niels Bohr, one of the founding fathers of quantum theory, introduced the principle of
2 complementarity into quantum physics. He originally pointed out that this principle is what
3 distinguishes quantum from classical probability theory [21]. This distinction will be made more
4 explicit in the following section.

5 The principle of complementarity leads directly to the most well known principle of
6 quantum theory—the uncertainty principle [21]. This principle holds that when we are certain
7 about a quantum particle’s position, we are necessarily uncertain about its momentum, and *vice*
8 *versa*. Placed in a psychological context, the uncertainty principle becomes relevant because a
9 person’s understanding of two events, such as two different politicians or two different
10 perspectives on a matter, requires changing from one point of view to another, and the two points
11 of view can imply incompatibility. For example, suppose you are planning a trip with a friend
12 and need to select a trip from a set of alternatives. For a given trip, you can judge how much you
13 will enjoy the trip yourself from your own perspective, and also judge how much your friend will
14 enjoy it from his or her perspective. The intuition behind the uncertainty principle is that after
15 clarifying your friend’s position, you may become uncertain about your own; likewise, after
16 clarifying your own position, you may become uncertain about your friend’s. In other words, the
17 uncertainty principle entails that it is not possible to be simultaneously decided on the matter
18 across both your and your friend’s perspectives. Such events (e.g., perspectives) are deemed
19 incompatible simply because they cannot be jointly considered simultaneously. The reason for
20 this relates to another basic principle of quantum theory, namely superposition. In the context of
21 our example, superposition means that when you are decided about a matter from one
22 perspective (e.g., you judge that you will enjoy the trip), your cognitive state has to be dispersed,
23 or indefinite, with respect to the other perspective (i.e., your friend’s enjoyment of the trip).

1 The principle of complementarity can be viewed as a constraint that bounds rationality.
2 This principle, along with the uncertainty and superposition principles, lead to key differences
3 between classical and quantum theories of probability [22]. These principles, we will argue, are
4 critical for understanding the limitations on human reasoning and decision making.

5 **Comparison of classical and quantum probability theories**

6 Classical probability theory developed over centuries from a grounding based on classical
7 physics. However, an axiomatic foundation for classical probability theory was not formulated
8 until the 20th century by Andrey Kolmogorov [23]. Modern applications of Bayesian inference
9 in cognitive science are derived from Kolmogorov’s theory. As we mentioned earlier, the
10 axiomatic foundation for quantum theory was formulated by John von Neumann around the
11 same time—an interesting coincidence [16]. Once the abstract mathematical principles were
12 identified and separated out from the physical content, it became clear that what quantum
13 physicists had discovered was a new probability theory [24]. In this section, we will compare the
14 two probability theories, side by side, to gain an understanding of where they are similar and
15 where they differ. This understanding is important when one considers the application of these
16 theories for modeling cognitive phenomena.

17 *Classical probability theory*

18 Classical probability theory is based on events, which in Kolmogorov’s theory,
19 correspond to subsets of a universal set. By way of illustration, let A denote the event that you
20 think you would enjoy the trip being considered, and let B denote the event that you think your
21 friend would enjoy the same trip. According to Kolmogorov’s probability theory, A and B are
22 subsets of a universal set that includes, as elements, all combinations of answers regarding what
23 you think about your and your friend’s enjoyment of the trip. Previously we saw how events can

1 be combined via conjunction (i.e., A and B). In Kolmogorov's theory, this conjunction is
2 represented as set intersection, $A \cap B$, which in our example represents the conjunction that you
3 think both you and your friend would enjoy the trip. In addition, events may be combined by set
4 union, $A \cup B$, which in our example represents the disjunction that you think you *or* you think
5 your friend would enjoy the trip. These definitions imply a Boolean logic for events. Given that
6 A is an event and B is an event, then $A \cap B$ is an event, and so is $A \cup B$. Recall that this logic of
7 events is commutative, that is, $A \cap B = B \cap A$. Another important property of this logic is the
8 distributive axiom: $A \cap (B \cup \sim B) = (A \cap B) \cup (A \cap \sim B)$, where $\sim B$ denotes the negation
9 of event B . In addition, classical models of cognition generally assume that a person has a
10 personal probability function p , which is used to assign probabilities to events according to the
11 rules summarized in Box 1.

12 *Quantum probability theory*

13 The corresponding foundations in quantum theory are markedly different. John von
14 Neumann replaced the set theoretic structure of classical theory with the projective geometric
15 structure of vector spaces using two separate steps [16]. First, the definition of events was
16 changed from one based on subsets of a universal set to another based on subspaces of a vector
17 space. Second, instead of using a function p to assign probabilities to events, von Neumann used
18 a state vector, S , to assign these probabilities as described in Box 2.

19 Mathematically, a vector is an arrow lying within a vector space. The state vector, S ,
20 might seem like an abstract idea, but when applied to cognitive science, it is analogous to the
21 distributed input across nodes in a connectionist neural network [25-26]. Mathematically, a
22 subspace is a geometric object (e.g., a ray, a plane, a hyperplane) lying within a vector space, and
23 each subspace corresponds to a projector that maps the state vector S onto the subspace. A

1 projector might seem like another abstract idea, but it also has a natural interpretation in
2 cognitive science: It maps the distributed input into a distributed output analogous to a
3 connectionist neural network [25-26] (see Figure 1). This mapping process is called projecting,
4 and the resulting output is called the projection. The probability assigned to an event equals the
5 squared length of the projection.

6 Let us provide some accompanying intuition by referring to Figure 2. Suppose the state
7 vector S represents your beliefs about enjoyment of a trip. First, consider the question about trip
8 enjoyment from your self-perspective, as shown in Panel a. The probability of event A (you think
9 you will enjoy the trip) *or* event B (you think you will be neutral about the trip) is determined by
10 the projection of the state vector S onto the plane spanned by the A, B axes, represented by the
11 blue vector T . Projection is like shining a light from above and seeing the length of the shadow
12 onto the plane (i.e., projection vector T is the shadow in Figure 2-a); the longer the shadow the
13 higher the probability. Formally, the squared length of the projection T constitutes the probability
14 of deciding to choose either event A or B (which equals .833 in the example). Similarly, the
15 probability of event C (you think you will not enjoy the trip) is determined by the squared length
16 of the projection of S onto the axis C (which equals .167 in the example).

17 Now consider the trip's enjoyment from the perspective of your friend by referring to
18 Panel b of Figure 2. This change in perspective is accomplished by rotating the $A, B,$ and C axes
19 from the self-perspective (Panel a) to form the three axes U (you judge your friend will enjoy the
20 trip), V (you judge your friend will be neutral about the trip), and W (you judge your friend will
21 not enjoy the trip) from the other-perspective (Panel b). The degree of rotation between the two
22 perspectives is determined by the similarity between your self-perspective and friend-perspective
23 (i.e., less rotation means the perspectives are more similar). The probabilities of answers from

1 your friend's perspective are then determined by projecting the state S onto events defined by the
2 U , V , and W axes. For example, the probability that you think your friend will be neutral about
3 the trip equals the squared length of the projection of the state vector S onto ray V (which equals
4 .812 in the example). Note that if you decide that your friend will be neutral about the trip, then
5 your state vector is updated to align with ray V . Observe carefully the consequence of this: You
6 must now necessarily become undecided about your own enjoyment of the trip as rays A , B and
7 C , that represent your perspective, are all oblique with respect to ray V . Technically speaking,
8 being certain about event V forces you to be superposed with respect to the events A , B , and C , as
9 determined by the quantum principles of superposition and uncertainty described earlier.

10 Earlier we introduced Niels Bohr's principle of complementarity, and Figure 2 provides
11 an example of how this principle can be understood in terms of projections. If first we project the
12 state S onto the A , B plane to produce the projection T , and then subsequently project T onto ray
13 V , then the squared length of the final projection equals .375. If instead, we first project the state
14 S onto ray V and then subsequently project the resulting projection onto the A , B plane, then we
15 acquire a different final projection with squared length of .406. In other words, reversing the
16 order of projections alters the final probability of two decisions taken in sequence. This in turn
17 implies that the events corresponding to these decisions are incompatible, and consequently these
18 events do not commute.

19 Note this does not mean that a person mentally rotates some kind of axes in N -
20 dimensional spaces. On the contrary, we think this is accomplished implicitly through some
21 interconnected neural network system [25-26], and quantum theory provides algorithmic level
22 predictions for this more complex neural implementation. On the one hand, neural networks are
23 not required to satisfy the axioms of quantum theory; on the other hand, the quantum algorithm

1 could be generated from a neural network [26].

2 In general, quantum theory defines events as subspaces. Each subspace has a
3 corresponding projector, where the associated logic of events is not necessarily Boolean [27]. In
4 particular, if two events A , B are incompatible, then the conjunction of events: A and B , cannot
5 be defined as they do not commute. Instead, only the sequence of events, A and then B , can
6 meaningfully be defined. This constitutes a major difference from classical probability theory
7 where the intersection of events is always defined and events are always commute, even if the
8 events are distinguished by time (e.g., “ A at time 1” and “ B at time 2” is equivalent to “ B at time
9 2” and “ A at time 1”). Further, in quantum theory, if event A is incompatible with event B , then
10 the distributive axiom also fails because the probability of event B is no longer equal to the
11 probability of A and then B plus the probability of $\sim A$ and then B .

12 **Empirical support for quantum cognition**

13 Why use quantum probability theory? After all, the prevalence of the Bayesian models is
14 testament to the success of classical probability theory in modeling cognition. Despite this
15 success, however, there has been a steady accumulation of puzzling, even paradoxical, cognitive
16 phenomena that violate the axioms upon which classical probability theory (and hence Bayesian
17 inference) is based. Thus far, these violations have been explained using heuristic rules such as
18 the representativeness heuristic and the anchoring-and-adjustment heuristic. Rather than
19 resorting to heuristics, quantum cognition successfully accounts for these violations using a
20 coherent, common set of principles. Although this review focuses on judgment and decision
21 making, we briefly highlight the expressive power of quantum models by pointing out that they
22 have been applied to a broad range of cognitive phenomena, including perception [28-29],
23 memory [30-32], conceptual combinations [33-36], attitudes [37-38], probability judgments [39-

1 42], causal reasoning [43], decision making [44-50], and strategic games [51-52]. It is not
2 possible to survey the myriad of applications in this review. We will restrict our attention to a
3 representative set of examples, which intuitively illustrate the basic quantum principles
4 introduced previously.

5 *Probability judgment errors*

6 Decades of research on human judgment have uncovered a full spectrum of so-called
7 irrational phenomena that deviate substantially from what would be considered normatively
8 correct according to classical logic and probability theory [39]. A popular example is “the Linda
9 problem.” As describe in Box 3, participants read a description of a liberal female college
10 student named Linda and are asked to judge the probability of a series of statements about her
11 after she graduated. This extensively studied experimental paradigm has shown that human
12 participants consistently rate the probability of the conjunction (being a feminist and bank teller)
13 to be greater than that of its constituent event (being a bank teller). This probability judgment
14 error is so robust that it has been named the conjunction fallacy, and was originally explained by
15 the representativeness heuristic [53].

16 According to quantum cognition, a key to explaining the conjunction fallacy is the
17 incompatibility between events—in the case of the Linda problem, that Linda is a bank teller and
18 that she is a feminist [39]. Referring to Panel a in Figure 3, suppose the person considers the
19 event that Linda is a bank teller. The probability of this decision is defined by the green
20 projection from the state S down onto the red B axis (B stands for bank teller). Observe that the
21 projection is short, indicating a low probability (.024 in the example). If the person makes this
22 decision, the cognitive state S collapses onto the axis B , reflecting that they have decided that
23 Linda is a bank teller. Note carefully that as illustrated in the figure, the person must now

1 necessarily be uncertain about whether Linda is a feminist because the axis B that corresponds to
2 the current cognitive state is suspended between the two vectors, F and $\neg F$ (F stands for
3 feminist). The hallmark of incompatibility is the state of indecision from one perspective (e.g.,
4 the feminist perspective) when a decision is taken from another (e.g., the bank teller perspective).

5 Now consider the probability of the conjunction of events that Linda is a feminist and
6 bank teller (F and B), which as explained in the previous section, must be considered
7 sequentially (F and then B) because F and B are incompatible. More specifically, the probability
8 of the conjunction is determined by first projecting the state S onto the axis F and then projecting
9 this result onto the axis B (following the black lines in the figure). Inspection of the figure shows
10 that the result of this two-step sequence of projections is longer (a .093 probability in the
11 example) than that obtained from event B alone. Therefore, we can intuitively appreciate how
12 these incompatible perspectives naturally allow the conjunction of events to have a higher
13 probability than a single constituent event, thus explaining the conjunction fallacy in a simple
14 and axiomatic way, without recourse to *ad hoc* heuristics.

15 The basic quantum model underpinning the conjunction fallacy also readily explains the
16 disjunction fallacy [39, 54]. Furthermore, this model makes new *a priori* predictions [39, 41].
17 Foremost among them is the consequence that incompatible judgments and decisions must entail
18 order effects. More specifically, the conjunction fallacy only occurs when the decision of Linda
19 being a feminist, or not, is evaluated before the decision of whether she is a bank teller. Indeed,
20 the conjunction fallacy has been found to depend on this order [55]. Order effects are central to
21 quantum theory, and we will review them next.

22

23 *Order effects on attitudes, inference, and causal reasoning*

1 Order effects are pervasive in human cognition, such as in attitude judgments [18-19, 37],
2 inferences [40], and causal reasoning [43]. An interesting example is the results of a 1997 poll in
3 the U.S. concerning public opinions on the characters of Bill Clinton and Al Gore [56]. Half of
4 the 1,002 nationally sampled respondents were asked: “Do you generally think Bill Clinton is
5 honest and trustworthy?” Subsequently, they were asked the same question about Al Gore. The
6 other half of respondents answered exactly the same questions, but in the opposite order. The
7 results exhibited a striking order effect: The proportion saying “yes” to both questions
8 significantly increased when Gore was judged first.

9 Quantum theory provides a natural account for question order effects in terms of
10 incompatibility [37, 57]. Referring to Panel b in Figure 3, first, consider the probability of “yes”
11 to both questions when Clinton is judged first. This is obtained by first projecting (following the
12 black lines) the state S down onto the blue horizontal Clinton axis and then projecting the result
13 to the red Gore axis, which produces a low probability (.173 in the example). Next, consider the
14 probability of “yes” to both questions when Gore is judged first. This is obtained by first
15 projecting (following the green lines) the state S to the red Gore axis and then projecting the
16 result down to the blue Clinton axis, which produces a higher probability (.487 in the example).

17 On the basis of the preceding examples, criticism might arise that the quantum model
18 lacks predictive power and only explains order effects in a *post hoc* manner. This criticism is
19 countered by the fact that the quantum model makes a precise, *a priori* prediction of a very
20 special pattern of order effects, called the QQ equality [37, 57]:

$$21 \quad [p(C \text{ and then } \sim G) - p(\sim G \text{ and then } C)] = -[p(\sim C \text{ and then } G) - p(G \text{ and then } \sim C)],$$

22 where for example, $p(C \text{ and then } \sim G)$ is the probability of saying “yes” to Clinton and then
23 “no” to Gore. Basically, the QQ equality predicts a surprising regularity in question order effects.

1 This is a completely general prediction: It must hold for any pair of questions measured back to
2 back; it must hold for any dimension N for the vector space; it must hold for any rotation of the
3 axes; it must hold for compatible and for incompatible events; it must hold regardless of initial
4 state; and it must even hold when averaging across people with different state vectors (see [37,
5 57] for proof). In short, the QQ equality is an exceptionally strong *a priori* prediction. Recent
6 research has shown that it was statistically supported across 70 national field experiments that
7 examined question order effects using a wide range of topics [37] (see Figure 4).

8 The quantum model is not the only model that can account for order effects. Another
9 traditional model is the anchoring-and-adjustment model based on the heuristics approach [58].
10 However, anchoring-adjustment models failed to account for the empirical patterns of order
11 effects and QQ equality observed in the 70 experiments mentioned above [37]. In addition, the
12 anchoring-and-adjustment model fell short of the quantum model when the two were
13 quantitatively compared in experiments investigating order effects on inference [40]. The general
14 finding of the experiments is that recent evidence has greater impact than early evidence [40],
15 which is uncorrelated with memory recall [59]. The anchoring-and-adjustment model failed to
16 even reproduce the correct ordering of the size of the order effects across the experimental
17 conditions, whereas the quantum model accurately reproduced all of the order effects [40].
18 Similar findings favoring the quantum model were also obtained using a causal reasoning
19 paradigm [43]. Although we have emphasized applications to order effects, quantum theory has
20 important applications to many other cognitive phenomena, including empirical violations of the
21 classical law of total probability (see Box 1), as discussed next.

22

23 *Violations of rational decision making*

1 One of the most important rational axioms of decision-making in classical theory is
2 called the “sure thing” principle [5]. It states that if you prefer action A over B under the state of
3 the world X, and you also prefer action A over B under the opposite state of the world $\sim X$, then
4 you should prefer action A over B even if the state of the world is unknown. Violations of the
5 sure thing principle produce violations of the basic classical law of total probability, which is the
6 foundation of Bayesian and Markov models, and thus holds an important role in modeling
7 cognition. This principle has been directly tested by making an innovative modification of the
8 well-known prisoners’ dilemma (PD) game [60]. In the typical PD game (see Box 4), each player
9 chooses to either cooperate or defect, and the two players move simultaneously without knowing
10 each other’s move. The payoffs are arranged so that defection is the dominant choice. The key
11 innovation for testing the sure thing principle was to include trials in the game that informed a
12 player of the opponent’s move before acting. What happened was quite surprising: When
13 informed that the opponent defected, the players defected on 97% of the trials; and when
14 informed that the opponent cooperated, the players continued to defect on 84% of the trials; but
15 when the opponent’s action was unknown, the players only defected on 66% of the trials [60]. In
16 other words, many players defected when the opponent’s action was known, but they changed to
17 cooperate when it was unknown. These results are shown to be robust, and present a clear
18 violation of the law of total probability. According to this law,

19
$$p(\text{Player Defects}) = p(\text{Opp Defects}) \cdot p(\text{Player Defects}|\text{Opp Defects})$$
$$+ p(\text{Opp Cooperates}) \cdot p(\text{Player Defects}|\text{Opp Cooperates}).$$

20 That is, the probability of defection when the opponent’s action is unknown should equal a
21 weighted average of the probabilities for the two cases when the opponent’s action is known.

22 Contrary to this classical law, the probability that the player defected in the unknown condition

1 fell far outside the bounds of any weighted average. These findings have been interpreted within
2 the heuristic framework as a failure of consequential reasoning [60]. Quantum theory, however,
3 provides a simple, axiomatic explanation based on the same principles of incompatibility as used
4 in the previous examples [45].

5 Violations of the law of total probability occur in many other applications, such as in
6 experiments investigating the interference of categorization on subsequent decision-making [49].
7 In the experiments, participants were shown faces, and on some trials they were asked to
8 categorize them as “good” guys or “bad” guys, and then decide to “attack” or “withdraw” (the
9 categorization-decision condition), and on other trials they only had to decide to “attack” or not
10 without explicitly categorizing a face (the decision-alone condition). They were usually (e.g.,
11 70% of the trials for both conditions) rewarded for attacking bad guys and withdrawing from
12 good guys. As expected, if the person categorized the face as a good guy, then the probability of
13 attacking was low; if the face was categorized as a bad guy, the probability of attacking was
14 much higher. Surprisingly, however, the probability of attacking without categorization (in the
15 decision-alone condition) exceeded the probability to attack when the face had been categorized
16 as a bad guy (in the categorization-decision condition). Once again, this is a violation of the law
17 of total probability, because according to this law,

$$18 \quad p(\textit{Attack}) = p(\textit{Good Guy}) \cdot p(\textit{Attack}|\textit{Good Guy}) + (\textit{Bad Guy}) \cdot p(\textit{Attack}|\textit{Bad Guy}).$$

19 Contrary to this law, the experiments found that the probability of attacking for the decision-
20 alone condition falls outside the bounds of any weighted average of the probabilities conditioned
21 on the categories.

22

23 Quantum theory once again uses the principle of incompatibility to provide a

1 straightforward account of violations of the law of total probability [45, 49]. As illustrated by
2 Panel c in Figure 3 and using the categorization-decision example, the probability of attacking in
3 the decision-alone condition is determined by the projection from the state vector S down to the
4 axes for the attack decision, which produces a probability of .875. If the person first categorizes
5 the face as a bad guy, then the state collapses onto this category to form a new state, which is
6 now aligned with the red “bad guy” axis. The probability of attacking, given the face is
7 categorized as a bad guy, is then determined by projecting from the state vector aligned with the
8 red “bad guy” axis down to the horizontal blue axis representing the attack action, which
9 produces a probability of .603. Thus, the probability to attack (.875) in the decision-alone
10 condition is higher than the higher bound of the weighted average (.603).

11 Critics might argue that quantum models’ ability to account for all these findings relies
12 on being more complex than their traditional counterparts. This criticism has been directly
13 addressed by performing a rigorous quantitative comparison of quantum vs. previously
14 successful traditional, classical decision models using a Bayesian model comparison method
15 [61]. Note that model complexity depends not only on the number of model parameters but also
16 on its functional flexibility [62]. The Bayesian model comparison method evaluates models with
17 respect to their accuracy, parsimony, and robustness. In the model comparison [61], the Bayes
18 factor strongly favored the quantum model over the traditional decision models, suggesting the
19 quantum model is more accurate and robust without being more complex than models based on
20 classical probability theory.

21

22

23 *Summary*

1 By means of three simple, intuitive examples, this review illustrates how some seemingly
2 diverse and puzzling cognitive phenomena can be explained by a common set of underlying
3 principles drawn from quantum theory. Of course, it may be possible to construct a traditional
4 model for each of these findings alone—for example, support theory [63] accounts for the
5 conjunction fallacy but not the other two findings. However, the real challenge is to find a single
6 coherent explanation for them all. Figure 3 demonstrated how quantum theory accomplishes this
7 challenge—using simple 2-dimensional “toy” models for ease of exposition. The quantum
8 models that were actually used to account for all the quantitative details related to these
9 empirical findings require more than just two dimensions. However, the principles in the more
10 complicated models are identical to those illustrated in the “toy” examples. Box 5 provides a
11 general summary comparison of Bayesian versus quantum models of cognition.

12 **Concluding remarks**

13 This review began by asserting that there are at least two viable ways to formulate
14 probabilistic models of cognition—one using classical probability theory and another using
15 quantum probability theory. We do not wish to leave the impression that these two theories are in
16 strict conflict. In fact, although their formulations are emphatically different, they do agree in
17 many cases. In particular, there is perfect agreement when all the events under consideration are
18 compatible. The need for the quantum approach only arises when incompatible events are
19 involved, which necessarily imposes a sequential evaluation of the events (see Box 2). This
20 incompatibility produces superposition states of uncertainty that result in violations of some of
21 the important laws of classical probability theory.

22

23 As a growing new field, quantum cognition also raises many new questions for cognitive

1 scientists and psychologists to address (see Box 6). One is about rationality. Classical probability
2 theory may provide an upper bound that achieves optimal performance irrespective of
3 computational costs and resource limitations. Quantum models may provide a more realistic
4 bound that performs close to optimal but with fewer computational demands. Consider, for
5 example, a strategic game involving yourself and $n - 1$ other players, and each player can choose
6 one of K actions. If human cognition directly implements classical probability theory (i.e., it
7 treats all events as compatible), then K^n joint probabilities are required to represent your beliefs
8 regarding the actions that could be taken by yourself and the other $n - 1$ players, producing an
9 exponential growth in dimensionality. If instead, human cognition applies a new incompatible
10 perspective to each player, then all of the required probabilities can be assigned by using a single
11 state vector that is evaluated with respect to different bases within a fixed K -dimensional space.
12 Using limited cognitive resources [75], incompatibility provides humans the means for
13 answering an unlimited number of questions, thus promoting parsimony and cognitive economy
14 [76]. However, the use of incompatibility comes at the cost of introducing non-commutativity
15 and sequential effects. Our view is that incompatibility of events provides an effective solution
16 to bounded resources, which is the reason for bounded rationality, and for this reason, we argue
17 that incompatibility is ubiquitous in psychology [77].

18

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22 authors contributed equally to this article.

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Figure Legends

5

6 **Figure 1. Cognitive science interpretation of a projector P .**

7 The state labeled S is a distributed representation across a set of input nodes. The projector P is
8 the matrix of weights connecting input nodes to output nodes. The inputs are mapped by the
9 connections to the output nodes to produce a distributed representation of the projection labeled
10 T . The probability of an event equals the squared length of the projection, $\|T\|^2$. This mapping is
11 analogous to a connectionist network, except that the values assigned to the input and output
12 nodes are not restricted to be positive real numbers as required by standard connectionist
13 networks.

14

15

16 **Figure 2. A hypothetical example to illustrate the quantum principles of complementarity,** 17 **uncertainty, and superposition.**

18 Hypothetical example using a three-dimensional vector space to represent three possible answers
19 to the trip enjoyment question. Panel a shows the representation of the three answers to the
20 enjoyment question from the self-perspective (in black). Panel b shows the representation of
21 these answers from the other-perspective (in black) that is rotated from the self-perspective (in
22 light grey). Event A represents the event “you will enjoy the trip,” B represents “you are neutral
23 about the trip,” and event C represents “you will not enjoy the trip.” The event A is represented

1 by the subspace defined as the ray or axis A in the left panel; likewise, for events B and C . Axes
2 U , V , and W represent these same three events but based on taking your friend's perspective.
3 Within each panel, the blue vector labeled S represents the cognitive state of the person who
4 makes the judgments. The event that A or B (you will enjoy or be neutral about the trip) occurs is
5 represented by the flat plane formed by the A , B axes. In panel a , the vector labeled T in the A , B
6 plane represents the projection on the subspace for the event A or B from the self-perspective,
7 and the squared length of the projection T is the probability of event A or B . Similarly, in panel b ,
8 the vector labeled R represents the projection on the subspace V from the other-perspective, and
9 the squared length of the projection R is the probability of event V (your friend will be neutral
10 about the trip).

11

12 **Figure 3. Three example applications of a cognitive model based on quantum probability**
13 **theory.**

14 Using a small set of coherent quantum probability rules, the model explains various empirical
15 findings that are puzzling to classical probability theory. Panel a illustrates the application to the
16 conjunction fallacy paradigm [39,41]. The feminist perspective is represented as a two-
17 dimensional vector space where the blue axis F corresponds to the decision "Linda is a feminist"
18 and $\neg F$ corresponds to "Linda is not a feminist." The same two-dimensional vector space, but
19 with rotated axes (the red axes), corresponds to the perspective of Linda being a bank teller (B),
20 or not ($\neg B$). Initially, the cognitive state of the decision maker is represented by the magenta
21 colored vector S , which is suspended between both sets of axes.

22 Panel b illustrates the application to question order effects [37, 57]. The horizontal blue axis in
23 the figure represents the event "yes" to the Clinton question, and the vertical blue axis represents

1 the “no” answer to the question. The two orthogonal red axes are used to represent the answers to
2 the Gore question, which are rotated 45 degrees (in this simple illustration) with respect to the
3 blue axes for the Clinton question. The initial attitude state of the respondent before answering
4 the two questions is represented by the magenta colored vector labeled S .

5 Panel *c* illustrates an application to the categorization-decision paradigm [49]. The horizontal
6 blue axis is used to represent the “attack” action, and the vertical blue axis is used to represent
7 the “withdraw” action. The categorization responses of “good guy” or “bad guy” are represented
8 by the red axes, which are rotated with respect to the blue axes. The magenta colored vector S
9 represents the state of the decision maker before making any categorization, which is superposed
10 with respect to categories.

11

12 **Figure 4. An empirical test of the QQ equality.**

13 An empirical test of the QQ equality using 70 national field experiments in the U.S. (in addition
14 to two lab experiments) [36]. Each point in this figure represents an order effect from one side of
15 the QQ equality plotted as a function of the order effect shown on the other side. The QQ
16 equality predicts that these points should all be on the straight line that has a slope equal to
17 negative one and intercept equal to zero. The observed points fall closely along this line with a
18 correlation equal to $r = -.82$.

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Additional Materials (Glossary, Text Boxes, and Outstanding Questions)

Glossary

Bayesian models of cognition. Bayes rule is a simple theorem that follows from the classical probability definition of conditional probability. Suppose $\{H_1, \dots, H_N\}$ is a set of hypotheses that you wish to evaluate, and D is some data that provide evidence for or against each hypothesis. Then according to the definition of conditional probability (see Box 1), $p(H_i|D) = p(H_i \cap D)/p(D)$. Bayes rule uses the classical definition of joint probability to rewrite the numerator on the right hand of the equation: $p(H_i \cap D) = p(H_i) \cdot p(D|H_i)$; and Bayes rule uses the law of total probability to rewrite the denominator: $\sum_j p(H_j) \cdot p(D|H_j)$. Bayesian models of cognition use these rules to construct models that predict how people make complex inferences from a set of observations [6,7].

Compatibility. Two questions are compatible if they can be answered simultaneously, or even if they are answered sequentially, the order does not matter; two questions are incompatible if they have to be asked sequentially and the order does matter. The principle of complementarity posits that some questions are incompatible, and these incompatible questions provide different perspectives for understanding the world, and these different perspectives are needed for a complete understanding of the world. Classical probability models usually assume *unicity*, which means all events can be described within a single compatible collection of events. In comparison, incompatible events are unique to quantum theory, which does not impose the principle of unicity.

Conjunction fallacy. Classical probability theory usually assumes that events are as subsets of a single sample space. This implies that the probability of an event A can never be less than the probability of the conjunction of A with another event B (“ A and B ”): $p(A) \geq p(A \cap B)$. However, violations of this law of classical probability, called the “conjunction fallacy”, have been found in empirical studies. The most well known empirical study is the Linda problem described in the review [e.g., 53], where human subjects rated the conjunction to be more probable. A quantum model has been proposed which explains the conjunction fallacy, along with other paradoxical findings [39, 41].

Contextuality. Constructing a classical probabilistic model involves defining relevant variables, which in turn form the basis of a joint probability distribution over the variables. However, research on entangled quantum systems has taught us that we cannot always assume the existence of joint distributions, and this approach to constructing probabilistic models can fail when applied to the observed data. This failure has come to be known as “contextuality.” It refers to the inability to construct the joint distribution over the variables.

1 **Disjunction fallacy.** The classical probability theory also implies that the probability of the
2 disjunction of an event A with another event B (“ A or B ”) can never be less than the probability
3 of the event A : $p(A) \leq p(A \cup B)$. Violations of this classical probability rule, called “disjunction
4 fallacy,” have been found in empirical studies [e.g., 54]. The same quantum cognition model
5 used to explain conjunction fallacy also explains the disjunction fallacy [39, 41].
6

7 **Dutch book argument (DBA).** Decision scientists and probability theorists use the Dutch book
8 argument to show that classical probability theory is a rational theory. The idea originated with
9 Bruno de Finetti, who proposed a game between a bookmaker and a better, where the bookmaker
10 provided stakes for bets that reflected his probability of winning. The better could make a Dutch
11 book against the bookmaker if the bookmaker’s stakes for individual bets were chosen in a way
12 that the sum across bets guaranteed that the better would win money and the bookmaker would
13 lose money in every state of the world. If the bookmaker chooses stakes that satisfy an additive
14 measure (items 3,4 in Box 1), then no Dutch book can be made against the bookmaker.
15

16 **Hilbert space.** A Hilbert space is an abstract and complete vector space defined on the complex
17 field and possessing the operation of an inner product (or dot product). It is named after the
18 famous mathematician David Hilbert. It extends vector algebra and calculus from the two-
19 dimensional Euclidean plane and three-dimensional space to spaces with an arbitrary number of
20 dimensions, including spaces of infinite dimensions. A finite Hilbert space is an N -dimensional
21 vector space defined on a field of complex numbers and endowed with an inner product.
22

23 **Superposition.** Superposition is a basic principle of quantum probability theory. Classical
24 probability theory assumes that at any moment, a system is in a definite state with respect to
25 possible states. This definite state can change stochastically across time, but at each moment, the
26 state is still definite, and the system produces a definite sample path. In contrast, quantum
27 probability theory assumes that at any moment, a system is in an indefinite (technically
28 dispersed) superposition state until a measurement is performed on the system. To be in a
29 superposed state means that all possible definite states have the *potential* for being actualized,
30 but only one of them will *become* actual upon measurement. The concept of superposition
31 resonates with the fuzzy, ambiguous, uncertain feelings in many psychological phenomena.
32

33 **The law of total probability.** In classical probability theory, the law of total probability is a
34 fundamental rule relating marginal probabilities to conditional probabilities. It is derived from
35 the distributive axiom of Boolean logic: If $\{A, B, C\}$ are events, then, $A \cap (B \cup C) =$
36 $(A \cap B) \cup (A \cap C)$. Define $p(A)$, $p(B)$, and $p(\sim B)$ as the marginal probability of event A , B , and
37 $\sim B$, respectively; and define $p(A|B)$ and $p(A|\sim B)$ as the conditional probability of event A
38 conditioned on knowing event B and $\sim B$, respectively. Then the law of total probability is,
39 $p(A) = p(B)p(A|B) + p(\sim B)p(A|\sim B)$. This law provides the foundation for inferences with
40 Bayes networks. In some experiments, $p(A)$ is estimated from one condition, and $p(B)p(A|B) +$
41 $p(C)p(A|C)$ is estimated from another condition, and violations of this classical law have been
42 found [e.g., 49, 60].
43

44 **The “sure thing” principle.** Savage [5] introduced the “sure thing” principle as a normative
45 principle governing rational decision making. According to this principle, if under the state of the
46 world X , a person prefers action A over B , and if under the complementary state of the world *not*

1 X , the person also prefers action A over B , then the person should prefer action A over B even
 2 when she/he does not know the state of the world. Violations of the sure thing principle have
 3 been empirically found [e.g., 60]: When A is preferred over B for each known state of the world,
 4 the opposite preference occurs when the state of the world is unknown.

5
6
7 **Box 1. Some key axioms, definitions, and theorems of classical probability theory.**

- 8 1. Events are subsets of a universal set U . Events, such as A and B , are subsets of U .
- 9 2. The state of the cognitive system is represented by a function p defined on the subsets in U
10 and the probability of an event A equals $p(A)$.
- 11 3. $p(A) \geq 0$, and $p(U) = 1$.
- 12 4. If $A \cap B = \emptyset$, then $p(A \cup B) = p(A) + p(B)$.
- 13 5. The probability of event B given A equals $\frac{p(A \cap B)}{p(A)}$.
- 14 6. Law of total probability: $p(B) = p(A \cap B) + p(\sim A \cap B)$.

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18 **Box 2. Some key axioms, definitions, and theorems of quantum probability theory.**

- 19 1. Events are subspaces of a Hilbert space \mathcal{H} . Events, such as A and B , correspond to subspaces
20 \mathcal{H}_A and \mathcal{H}_B , respectively of \mathcal{H} . Associated with these subspaces are projectors P_A and P_B .
- 21 2. If their projectors are commutative, that is, $P_A P_B = P_B P_A$, then the events A and B are
22 compatible. Otherwise, they are incompatible.
- 23 3. The state of the cognitive system is represented by a unit length vector S in the vector space,
24 and the probability of event A equals $\|P_A \cdot S\|^2$.
- 25 4. $\|P_A \cdot S\|^2 \geq 0$ and $\|P_{\mathcal{H}} \cdot S\|^2 = 1$.
- 26 5. If $P_A P_B = 0$, then $\|(P_A + P_B) \cdot S\|^2 = \|P_A \cdot S\|^2 + \|P_B \cdot S\|^2$.
- 27 6. Probability of event B given A equals $\frac{\|P_B \cdot P_A \cdot S\|^2}{\|P_A \cdot S\|^2}$.
- 28 7. Violation of the law of total probability: $\|P_B \cdot S\|^2 \neq \|P_B \cdot P_A \cdot S\|^2 + \|P_B \cdot P_{\sim A} \cdot S\|^2$.

29
30
31 **Box 3. The Linda problem.**

32 The Linda problem is a typical example showing conjunction fallacy [53]. In the experiments,
33 participants are given the following scenario:

34 Linda is 31 years old, single, outspoken, and very bright. She majored in
35 philosophy. As a student, she was deeply concerned with issues of
36 discrimination and social justice, and also participated in anti-nuclear
37 demonstrations. Which of the following is more probable?

38 (a) Linda is a bank teller.

39 (b) Linda is a bank teller and is active in the feminist movement.

40 According to classical probability theory, the probability of the conjunction of events (b) can
41 never exceed the probability of one of its constituent events (a). However, many studies have
42 robustly shown that human participants consistently rate option (b) as more probable than (a).

43
44
45 **Box 4. Payoff matrix for the prisoner's dilemma game.**

1 In a typical prisoner's dilemma game, the payoff matrix is set up in the way that no
 2 matter what move your opponent makes, you are better off to defect; the same is true for your
 3 opponent. The following table shows an example.

| | <i>the opponent defects</i> | <i>the opponent cooperates</i> |
|----------------------|---------------------------------------|---------------------------------------|
| <i>you defect</i> | You get 10, and the opponent gets 10; | You get 25, and the opponent gets 5; |
| <i>you cooperate</i> | You get 5, and the opponent gets 25; | You get 10, and the opponent gets 10. |

4 **Box 5. Comparison of Bayesian and quantum models of cognition**

5

| | |
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| <p>6 Bayesian models of cognition [6,7] have 7 been established for a longer period of time. 8 9 Bayesian models are based on a probability 10 theory that is more conventional and more 11 familiar to most researchers. 12 13 14 Bayesian models are derived from a set of 15 axioms that may be too restrictive for 16 describing all of human judgments and 17 decision making. 18 19 Bayesian models have many successful 20 applications in areas such as concept 21 learning and causal reasoning. 22 23 24 25 26 Stronger than usual evidence is required to 27 encourage researchers to accept the newer 28 ideas of quantum theory over the more 29 established Bayesian models. 30 31 It may be possible to develop a classical 32 model to account for all of the puzzling 33 findings that are used to support quantum 34 cognition. 35 36 37 Bayesian models may be considered the 38 normative standard without regard to 39 computational costs and resource 40 limitations. 41 42 43 44</p> | <p>42 Quantum models of cognition [8-10] are 43 recently developed. 44 45 Quantum models are based on a probability 46 theory that is unconventional and unfamiliar 47 to many researchers, especially in the fields 48 of social and behavioral sciences. 49 50 Quantum theory is based on a more relaxed 51 set of axioms that may better reflect human 52 reasoning and decision making under 53 uncertainty. 54 55 Although quantum models have been 56 applied to many different cognitive 57 phenomena, they have mainly focused on 58 problems found in judgment and decision 59 research that are difficult for Bayesian 60 models to explain. 61 62 Tests of <i>a priori</i> predictions and quantitative 63 model comparisons are beginning to provide 64 strong evidence needed to justify quantum 65 models of cognition. 66 67 At this point in time, no such classical 68 model has been proposed. If such a classical 69 model is proposed, then rigorous model 70 comparisons are required to compare the 71 classical and quantum models. 72 73 Quantum models may be considered the 74 prescriptive standard that works effectively, 75 while at the same time obeying the 76 constraints of bounded rationality.</p> |
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3 **Box 6. Outstanding questions.**
4

- 5 • *What about dynamics of cognition and decision? In the review, we have only presented*
6 *the structural component of quantum theory. Can the Schrödinger wave equation be used*
7 *to describe the dynamic processes that lead to decisions? If so, how do quantum*
8 *dynamics differ from classical dynamics based on Markov processes [48]?*
9
- 10 • *Will contextuality create a major shift in how probabilistic models are viewed within*
11 *cognitive science? Constructing classical probabilistic models involves defining relevant*
12 *variables, which in turn form the basis of a joint probability distribution over the*
13 *variables. Does this joint distribution always exist? Pioneering researchers investigating*
14 *contextuality are beginning to question this assumption [32, 64-66].*
15
- 16 • *If the quantum cognition research program does not rely on the assumption that the brain*
17 *is some type of quantum computer, then how does the brain accomplish quantum-like*
18 *behavior? Scientists are still far from understanding the way mental states emerge from*
19 *the neural substrates. Is quantum physics related here in a significant way [67-70]? Or,*
20 *can quantum-like effects emerge from a classical neural network [71-73]?*
21
- 22 • *How to define rationality? Are quantum probability models rational or irrational?*
23 *Quantum probability, like classical probability, is an axiomatic system for assigning*
24 *probabilities to events, but the two systems rely on different axioms. Can either system of*
25 *axioms legitimately lay claim to be the norm for prescribing rational behavior in*
26 *reasoning, inference, and decision-making? Do quantum probabilities satisfy the Dutch*
27 *book argument [74]?*
28
- 29 • *If the world that we as humans experience is the macro-level world in which objects*
30 *behave to a large extent according to the rules of classical physics, then why would*
31 *evolution result in a reasoning system based on quantum rather than classical*
32 *probability? Does everything in the macro-level world that we experience behave*
33 *according to classical probability theory? What about human beings as well as animals*
34 *with which we interact in this macro-world? Do conscious mental events obey rules of*
35 *classical physics?*
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