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Human Expertise, Knowledge, and  
Problem-Solving  
(Extended Version with Applications)

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# Quantum-Sapiens: The Quantum Bases for Human Expertise, Knowledge, and Problem-Solving\*

(Extended Version with Applications)

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**Abstract:** Despite the great promises and potential of quantum computing, the full range of possibilities and practical applications is not yet clear. In this contribution, we highlight the potential for quantum theories and computation to reignite the art and science of expert systems and knowledge engineering. With their grounding in uncertainty and unpredictability, quantum concepts are able to expand theoretical and practical boundaries of research and exploration. We demonstrate the advantages of using quantum logic and computation when applying expert knowledge such as the ability to ask imprecise (inherently probabilistic) queries and do so efficiently through large and complicated computational spaces by leveraging quantum concepts such as superposition, entanglement, parallelism, and interference to sustain and manipulate networks of quantum qubits. This, we argue, can provide non-insignificant computational speedups and enable more

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complex data representations and analysis. We then explore three practical applications and provide evidence for their quantum advantages – Scientific Discovery, Creativity and Breakthrough Thinking, Complex Systems, and Future of Sports – that we regard as largely unexplored in popular accounts of quantum theory; as such, we suggest these are low hanging fruit for the more-immediately feasible applications of quantum technologies.

**Keywords:** Quantum, Expert Systems, Knowledge, Problem-Solving

## 1 Introduction

Simply defined by Siler (2005), “expert systems are computer programs, designed to make available some of the skills of an expert to non-experts” (p. xii). In this sense, expert systems involve the transferral of expert human knowledge, experience, intuition, and reasoning to computers which may then be used to automate, train, and/or support complex human decision-making processes. Expert systems can result in considerable cost reductions, increased productivity, quality, and consistency, and reduction of uncertainty in decision-making systems. They also help to capture scarce industrial/organisational knowledge (Turban, 1988).

Despite a wealth of complex computational models and increasing numbers of expert decision-support systems, human experts are still highly sought after and used extensively to support serious, consequential decision making efforts as well as helping solve smaller, more everyday types of problems (Stehr, 2011). As Sriboonchitta et al. (2019) suggest, the best results are achieved when we ask imprecise rather than precise queries – those which experts typically ask – and we can leverage quantum theories to do so.

This paper explores the relationship between concepts in quantum theories to those of expert systems, creativity, problem solving, and scientific discovery. In doing so, we seek to uncover potential avenues for future theoretical and applied research outside of those usually mentioned in popular reports of quantum technologies. In the first section, we introduce quantum theory, mechanics, information theory, logic, and computation. Next, we question the current relevance of human expertise, reasoning, and decision making in the era of AI and quantum.

In the last section, we provide three domains that – in our estimation – present fruitful opportunities for the application of quantum concepts<sup>1,2</sup>.

## 2 Quantum Theories

In the classical sciences, systems are assumed to have mostly well-defined properties<sup>3</sup>. If all relevant pre-conditions are known, specific outcomes will occur time and time again, subject of course to any randomness driven by some known or unknown stochastic processes. In other words, systems and their behaviour are deterministic or probabilistic in nature. Quantum theory accepts the unpredictability of precise outcomes and recognises randomness as a fundamental concept in many complex systems (Peres, 2002), in a similar sense to classical probabilistic theories focused on modelling situations and decision making under uncertainty. Quantum theories are generally seen to better explain “cases of decisions under strong uncertainty, when utility theory fail (p.749)” (Yukalov et al., 2018), whilst retaining predictive capacity as opposed to the more descriptive analyses of classical probability theories. Ultimately however, placing greater focus on the evidence of irregularity and randomness has contributed to a deeper understanding in many fields across the hard and soft sciences alike (Mirowski, 1990).

While randomness is not unique to quantum theory, classical stochastic processes fall short of accounting for certain complex natural and human phenomenon such as the conjunction fallacy (i.e., an agent assigns a probability of two events occurring together that is greater than the probability of one event occurring alone) demonstrated famously by Tversky and Kahneman (1983). Tversky and Kahneman explained this via representative heuristics on their account that classical probability theory is not appropriate for understanding such judgements. Without resorting to heuristics, quantum theories recognise the contextuality dependence of the probability assessment and provide mathematical foundations which unlock unique benefits for the representation and evolution of context (i.e., the context in which measurement of a quantum observable takes place)(Ashtiani & Azgomi, 2015).

The mathematical formalism of quantum theory can be used to estimate the probabilities of certain events (e.g., a stock market crash, the emission of solar flare, or the position of an atom

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<sup>1</sup> This is an extended version of a paper (with the same title) which has been conditionally accepted for publication in *Technology Analysis & Strategic Management*. This extended version provides detail on three practical applications of quantum theory that we deem as low hanging fruit for more near-term quantum capabilities.

<sup>2</sup> That part was also originally peer-reviewed by *Technology Analysis & Strategic Management* but we had to delete it in the final journal version to meet the journal’s word limit.

<sup>3</sup> Not all classical sciences are deterministic, many exhibit properties that are more probabilistic in nature and hence, also contain some element of uncertainty and unpredictability, despite their classical foundations.

in space) (Englert, 2013). Rather than precise predictions, quantum theories provide insights into more imprecise queries, similar to those made by experts (Sriboonchitta et al., 2019). Born’s rule (1926) provides the link between mathematical formalisms and observed (measured) phenomena (events). The defining features of said events include localisation in time and space, irreversibility, and random realisation (Englert, 2013). Before we move any further, we provide our definitions for these quantum features and other quantum concepts in Table 1.

Table 1: Definitions of Quantum Concepts

Concept	Definition
Space-Time Localisation	An event having an approximate location in physical space and historical time (Haag, 2013).
Irreversibility	When an event is irreversible “it leaves a document behind, a definite trace” (Englert, 2013, p. 2).
Random Realisation	The unpredictability of an event due to the inherent randomness in which one of many possible events (each with a certain probability of occurrence) is eventually realised and not owing to missing or incomplete information (Englert, 2013).
Linearity	A function which satisfies the properties of additivity and homogeneity.
Entanglement	The values of certain properties of one system are correlated with the values that those properties will take in the other one of which it is entangled with. This can persist even with spatial and temporal separation.
Superposition	A mixed and indeterminate combination of finite states (e.g., 0 and 1) existing prior to some quantum measurements.
Non-locality	Used to describe correlated or entangled events which occur despite space-time separation.
Interference	Constructive or destructive interference of certain observables on others including itself.
Decoherence	The collapsing of a linear superposition (i.e., coherent) or potentiality states into any one of its possible states of actuality (e.g., when a coherent system interacts with or is disturbed by its environment such as during measurement).

Oracle	A “black box” operation used as input to another algorithm.
Indeterminacy	The assertion that the state of a quantum system does not determine a unique collection of values for all its measurable properties at any one time.

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## 2.1 Quantum Mechanics

Classical mechanics is an approximate theory of nature (Banks, 2019). The major difference between classical and quantum mechanics is a fundamental dissimilarity between the observed and unobserved states of an entity (e.g., an atom). In quantum mechanics, prior to observation (measurement), an entity is not constrained to existing in any precise position; but rather, exists in an indeterminate region of space. This may be within an area of greatest likelihood or expected likelihood, however, there is yet an underlying uncertainty and unpredictability in its exact positioning (Baaquie, 2013). Heisenberg (1962) coined the terms potentiality and actuality to describe the indeterminate (unobserved) and definite (observed) condition of a quantum entity, respectively. Each measurement transitions a quantum entity from a potentiality state to one of its many possible and definite conditions.

One could quite reasonably question how quantum indeterminacy is different at all from classical randomness. Classical probability fails to explain quantum indeterminacy because a specific quantum state does not exist independent of any measurement. Without measurement, a quantum state exists in some superposition of all possible states and a probability is assigned only to the likelihood of possible outcomes of the measurement process itself (Baaquie, 2013) rather than to some physically real, random variable as in classical probability.

Despite its complexity and often conceptually unfamiliar solutions, quantum mechanics has been widely successful and reliable in explaining many real-world phenomena (Englert, 2013). For example, the transistor was developed and operates on quantum principles and became an enabling technology for a host of others including practically all modern and dated digital electronics and communication technologies (Kolawole, 2020). Further, concepts and methods from quantum mechanics and probability have used to explain a growing list of complex human phenomenon such as human cognition and decision making (Ashtiani & Azgomi, 2015; Busemeyer & Bruza, 2012; Khrennikov, 2015; Pothos & Busemeyer, 2013), common sense (Noori & Spanagel, 2013), consciousness (Atmanspacher, 2004), and causal reasoning (Trueblood & Busemeyer, 2012).

## 2.2 Quantum Information

The physical nature of information implies that information abides by the laws of nature; in particular, those of quantum mechanics (Landauer, 1996, 1999). This view makes possible new and powerful tools of transmission and information processing by leveraging the principles of quantum mechanics such as linearity, entanglement, superposition, non-locality, interference, and indeterminacy (Galindo & Martin-Delgado, 2001). Classical information theory is concerned with information in binary (i.e., a state of zero or one), ternary (i.e., a state of zero, one or two, or when balanced negative one, zero or one), quaternary (i.e., a state of zero, one, two or three), and in general  $n$ -ary (i.e., a state of zero, one, two, three,  $\dots n - 1$ ) forms wherein bits (classical bits or c-bits) carry information from source to destination over some noisy or noiseless channel (Shannon, 1948). In quantum information theory, quantum bits (qubits) exist – prior to measurement – as a superposition of all possible states of the two classical states of zero and one (Schumacher, 1995). Somewhat counterintuitively, the superposition of one qubit carries only as much information as a classical bit. However, with two or more qubits we start seeing more quantum gains, a concept known as quantum parallelism which, as discussed later in Section 2.4, is at the foundation of the unprecedented power of quantum computers (Galindo & Martin-Delgado, 2001).

## 2.3 Quantum Logic

In the same way that classical computers can perform sequences of one- and two-bit operations (e.g., AND, NOT, and OR logic gates), quantum computers can perform sequences of one- and two-qubit quantum operations (e.g., XOR logic gate) (Bennett & Shor, 1998). Simply described, “a quantum logic gate is an input-output device whose inputs and outputs are discrete quantum variables” (p. 346). Any set of one- and two-qubit quantum logic gates can be used to construct a universal quantum computer and hence, perform any desired transformation on quantum variables (Lloyd, 1995). In other words, generalisable quantum gates can be ‘wired together’ to produce quantum logic circuits that can simulate any quantum phenomena and perform any computations (Deutsch, 1989) without the exponential slowdown which would, of course, be experienced by a classical computer (Feynman, 1982).

## 2.4 Quantum Computing

As early as the mid-1980s, Feynman (1982) suggested that certain quantum effects cannot be simulated efficiently on a classical computer. Indeed, there are also some important scientific problems for which quantum computers are suspected to be the only known means by which we can solve them practically (i.e., classical solutions may exist but are subject to either

excessive time or memory constraints) (Resch & Karpuzcu, 2019). Quantum computers can offer some reprieve for such problems and computations. Quantum superposition, as Moret-Bonillo (2018) explain, “(...) allows several operations to be performed simultaneously, depending on the number of qubits” (p. 165) hence, enabling large input vectors to be subjected, simultaneously, to (reversible) quantum logic gates and operations. “Computing classically in parallel means ‘at the same time’, while the quantum parallelism means ‘using the same space’, which also means there is no need in time synchronization (p. 1)” (Ablyev & Vasiliev, 2011). Hence, for classical systems, the amount of parallelism increases in direct proportion to system size whereas for quantum systems, it increases exponentially with size (Steane & Rieffel, 2000). This is a key differentiator between classical and quantum computers as Moret-Bonillo (2018) explains in other words:

The number of qubits indicates the number of bits there can be in superposition. With conventional bits, if we had a three-bit register there would be eight possible values, and the record could only take one of those values. On the other hand, if we have a vector of three qubits, the particle can take eight different values at the same time thanks to the quantum superposition. Thus, a vector of three qubits would allow a total of eight parallel operations. As expected, the number of operations is exponential with respect to the number of qubits (p. 165-166)

As discussed, the power of quantum algorithms mostly derives from harnessing the benefits of quantum parallelism (Deutsch & Jozsa, 1992) which is itself enabled by quantum concepts of superposition, entanglement (Rieffel & Polak, 2000), and interference. Together, as Steane and Rieffel (2000) suggest, “this massive parallelism, exponential in the number of particles used in the computation, (...) [enables quantum computers to] make any calculation on all values in roughly the same time an ordinary computer would take to make a calculation on a single value” (p. 40). The potential for this sort of computation in the ‘Big Data’ age is immense and intuitively obvious. The properties of quantum entanglement have also enabled promising technological applications such as quantum teleportation (Bennett et al., 1993), quantum encryption (Barz et al., 2012), quantum internet (Kimble, 2008), and quantum dense coding (Rieffel & Polak, 2000). In general, as Orus et al. (2019, p. 4) describes, a quantum algorithm is a sequence of five steps:

- “... 1. Encode the input data into the state of a set of qubits.
2. Bring the qubits into superposition over many states (i.e., use quantum superposition).



3. Apply an algorithm (or oracle) simultaneously to all the states (i.e., use quantum entanglement amongst the qubits); at the end of this step, one of these states holds the correct answer.
4. Amplify the probability of measuring the correct state (i.e., use quantum interference).
5. Measure one or more qubits.

It has been shown that for some computations (using the processes similar to that described above), quantum computers are capable of exponential speed-ups over classic computers with only a linear – as opposed to exponential in the case of classical computers – increase in physical space required to house such computational hardware (Deutsch & Jozsa, 1992). Further, for some problems, Grover’s algorithm can provide quadratic speedups not just over the naïve (brute force) classical algorithm but also over the more computationally efficient (less exhaustive) classical algorithms also. (Ambainis, 2004). In other words, quantum computers hold promise even for the more general search problems and methods. This is a great outcome as “even a small polynomial speed-up on average for these computationally difficult problems is of significant practical interest (p. 323)”(Rieffel & Polak, 2000) and hence, quantum computers and algorithms should at least be considered when performing certain complex computations for which quantum computers exhibit non-insignificant time or memory advantages. This can extend, for example, to hybrid quantum-classical systems. We direct the interested reader to Endo et al. (2020) for a well-covered review of hybrid quantum-classical computers, and Li et al. (2017) and Otterbach et al. (2017) for examples of practical applications – quantum optimal control and unsupervised machine learning, respectively.

One area of problem solving for which quantum computers can offer a unique advantage over classical computers is in search problems (Rieffel & Polak, 2000). In particular, Grover’s (1996) algorithm can utilise superposition to ask questions often posed by experts, such as: “is one of the earlier records containing the desired information” (Sriboonchitta et al., 2019) and use amplitude amplification to derive the most probable and/or (with well-designed algorithms) desirable outcomes (Ambainis, 2004). By doing so we can explore problem spaces which are too large or complex to be efficiently searched using a classical computer under reasonable time and memory constraints.

Other well-known quantum algorithms include Shor’s (1994) algorithm for efficient prime factorisation (a fundamental complexity to many modern day cryptography technologies), quantum counting algorithm (Brassard et al., 1998) for efficient counting of solutions for a given search problem, and the Harrow-Lloyd algorithm (Harrow et al., 2009) for solving linear

equations. Further, the ‘true’ randomness of quantum physics (Antonio & Lluís, 2016) could be used to implement truly random number generators in Monte Carlo methods of simulation (Antonio & Lluís, 2016) and provide quantum speedups as such (Montanaro, 2015). These random number generators are also at the heart of key quantum technologies including Quantum Key Distribution and Cryptography (Krithika, 2017). Artificial Intelligence (AI) algorithms – for example, see Dunjko and Briegel (2018), Zhaokai et al. (2014), and Aerts and Czachor (2004) – also benefit from the unique properties of quantum computing either by computational speedups, simplified search, or both.

Quantum potentiality states by their nature are unpredictable and highly susceptible to decoherence from both measurements and interactions (whether intended or unintended) with the environment. Further, these potentiality states must be maintained for some reasonable length of time to undertake the computation. Likewise, the ability to preserve and manipulate entangled states is at the source of both the power of quantum computers (and the computations they enable), and the difficulty experienced thus far in building them (Bennett & Shor, 1998). Thus to enable the practical use of quantum computing (including their use in search problems), further development and technological advances (and research funding) are required to build robust quantum computers with a sufficiently high numbers of qubits (Resch & Karpuzcu, 2019).

Novel and non-traditional programming techniques, such as quantum error correction coding, are expected overcome many outstanding issues with the fragility of maintaining potentiality states and the decoherence (collapsing) of these states following measurements (Rieffel & Polak, 2000). Unfortunately, most methods of quantum error correction coding require access to computers with many qubits that are capable of maintaining useful decoherence times (Endo et al., 2020). As Rieffel and Polak (2000) explain, these developments are also crucial to our ability to empirically assess the efficacy of using quantum algorithms over their classical counterparts:

(...) there is an exponential slowdown when simulating a quantum computer on a classical one, empirical testing of quantum algorithms is currently infeasible except in small cases. (...) Until sufficiently large quantum computers are built, or better techniques for analyzing such algorithms are found, the efficiency cannot be determined for sure(p.323).

As we gain access to more powerful, robust quantum machines and likewise, more sophisticated algorithms, the many promises of quantum computing will begin to be realised and verifiably so.

### 3 Is Human Expertise Still Alive or Relevant?

Contrary to the AI pioneers such as Herb Simon or Allen Newell, a second generation of AI scholars around Edward Feigenbaum and Ray Reddy were less interested in modelling precisely how human intelligence works, and more interested in knowledge representation and devising ways to help humans achieve things (McCorduck, 2019). Thanks to their work, knowledge representation became an important field of research, and expert systems, a promising application of technology.

The Dendral project – headed by Feigenbaum in collaboration with Lederberg – was one of the most prominent, successful, and long-standing AI research projects with more than one decade of continuously productive output (Lindsay et al., 1993). Owing to its success, in the following sections we trace through the history of Dendral-inspired knowledge engineering and expert systems theoretical and methodological developments. In Section 3.1 we introduce HEURISTIC DENDRAL – the first *inference machine* developed by the Dendral Project – and the ‘knowledge is power’ thesis of Dendral’s followers. In Section 3.2 we introduce a later, but no less innovative Dendral produce – MYCIN, the first *inference engine* – and discuss its flexible approach to reasoning and its ability to handle uncertainty. In Section 3.3 we highlight some of the major progresses and setbacks / downfalls of expert systems. Finally, in Section **Error! Reference source not found.** we propose some new hope for the furthering of knowledge engineering and expert systems in knowledge representation and how quantum computing can help.

#### 3.1 HEURISTIC DENDRAL and the Inference Machine

In his book *The Emotion Machine*, Minsky (2006) regards conceptualization as that which distinguishes us from other animals. Edward Feigenbaum was interested in creating models of thinking processes, and as a specific task environment, he selected the thinking process of scientists, “especially the processes of empirical induction by which hypotheses and theories were inferred from data” (Shortliffe & Rindfleisch, 2000). According to Feigenbaum, “[i]nduction is what we’re doing almost every moment, almost all the time” (McCorduck, 2019, p. 175). He identified the problem he was looking for after hearing Nobelists’ Joshua Lederberg’s talk about the problem of discerning the structure of a chemical compound from

knowledge of its atomic constituents and from its mass spectrogram, using knowledge employed by skilled chemists when interpreting mass-spectral data (Nilsson, 2009). Feigenbaum called it one of the most memorable scientific talks he ever attended (Feigenbaum, 1968). Together with Lederberg he gathered a robust team, including the philosopher Bruce Buchanan and later Carl Djerassi – best known for contributing to the development of the oral contraceptive pills – for investigations into how scientists interpret the output of mass spectrometers (McCorduck, 2019). The skilled chemists’ knowledge was represented as rules, and the group named their first program using this kind of knowledge the HEURISTIC DENDRAL; heuristics because it used knowledge from the chemists to control the search down process through the tree (Nilsson, 2009). Heuristics included the specific chemical knowledge in the form of experience and intuition (McCorduck, 2019). For example:

Rule 74 (Nilsson 2009, p. 199):

IF       The spectrum for the molecule has two peaks  
          At masses X1 and X2 such that:  
               $X1 + X2 = M + 28$   
              and  
              X1 – 28 is a high peak  
              and  
              At least one of X1 or X2 is high

THEN The molecule contains a ketone group

Programs developed by the Dendral project in the 1970s are still used by chemists today (Nilsson, 2009). Feigenbaum was interested in moving away from a focus on reasoning – such as Allen Newell and Herb Simon’s General Problem Solver – to knowledge as an important source of machine and human intelligence<sup>4</sup>: “Knowledge can be refined, edited, and generalized to solve new problems, while the code to interpret and use the knowledge – the reasoning, the inference engine – remains the same. This is one reason why, in the last few years, AI has become noticeably smarter. The amount of knowledge on the Internet available to Watson, Google Brain, or language-understanding programs (or scores of start-ups) has grown dramatically” (McCorduck, 2019, p. 177-178). He presented the importance of specific knowledge about the problem domain (i.e., the knowledge-is-power hypothesis) by calling it the knowledge principle (Nilsson, 2009):

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<sup>4</sup> McCorduck remembers Ed Feigenbaum’s visit to Carnegie Mellon in the 1970s, and his teasing AI and Herb with the line “Guys, you need to stop fooling around with toy problems” (McCorduck, 2019, p. 181).

“We must hypothesize from our experience to date that the problem solving power exhibited in an intelligent agent’s performance is primarily a consequence of the specialist’s knowledge employed by the agent, and only very secondarily related to the generality and power of the inference method employed. Our agents must be knowledge-rich, even if they are methods-poor” (p. 200).

### 3.2 MYCIN and the Inference Engine

The team discovered that the more you train the system, the better it got, and Buchanan was eager for Dendral to go further and make its own discoveries (McCorduck, 2019). The idea was to collaborate with additional scholars to build a computer program that consults with physicians about bacterial infections and therapy, leading to a program called MYCIN, a word coined by Edward Shortliffe (Nilsson, 2009). Shortliffe and Buchanan identified that physicians also appear to use IF-THEN reasoning: “IF the symptoms are such-and-such, THEN the cause is likely to be so-and-so” (Nilsson 2009, p. 230). An important part in the construction of expert systems is therefore interviewing experts (McCorduck, 2019; Nilsson, 2009) and deriving a consulting system that interacts with the users (e.g., physicians) who supply information (e.g., specific patient) (Nilsson, 2009). Shortliffe also decided to introduce certainty factors as the IF-THEN rules were hedged with uncertainty (Nilsson, 2009). Here is an example (Nilsson 2009, p. 231):

RULE036

PREMISE: (\$AND (SAME CNTXT GRAM GRAMEG)  
(SAME CNTXTM MORPH ROD)  
(SAME CNTXT AIR ANEAROBIC))

ACTION: (CONCLUDE CNTXT IDENTITY BACTEROIDES TALLY 0.6)

IF: 1) The gram stain of the organism is gramneg, and  
2) The morphology of the organism is rod, and  
3) The aerobicity of the organism is anaerobic

THEN: There is suggestive evidence (0.6) that the identity of the organism is bacteroides

Thus, the value 0.6 considers uncertainty, and thereby provides a degree of belief about the conclusions, incorporating some degree of ‘expert intuition’ rather than precise and certain knowledge. MYCIN also had the ability to explain its line of reasoning (McCorduck, 2019). For example: “Why did you ask whether the morphology of the organism is rod [?]. . . because

I am trying to determine whether the identity of the organism is bacteroids” (Nilsson 2009, p. 231). A core innovation of MYCIN was the way in which the reasoning process (using a rule “inference engine”) remained separate from the medical knowledge (the rules themselves, “knowledge base”). This provided flexibility in constructing new expert systems via changing the knowledge base but not the inference engine (Nilsson, 2009). Future programs encoded rules as partitioned semantic networks; rules could be linked together (inference networks); and inferences from rule premises to rule conclusions in the network were linked to Bayes’ rule probabilities by giving numbers following principles of probability theory (Nilsson 2010).

### **3.3 The Highs and Lows of Expert Systems**

Expert systems have been a very powerful tool for solving real-world problems (McCorduck, 2019); thus, not surprisingly, many new companies have developed such systems (Nilsson, 2009). The success of expert systems was due to their ability to solve narrowly- and well-defined problems (McCorduck, 2019), yet they were deployed across many business functions such as manufacturing, sales, engineering, diagnostics/maintenance, and corporate knowledge management (Feigenbaum et al., 1989). The downfall of expert systems and knowledge engineering lies in the difficulty (cost, time and effort) of developing such systems (Turban, 1988), their narrow scope of expertise and hence, fragility to novel problems (as opposed to more general knowledge systems which could contain hundreds of thousands or millions of linked concepts, facts, heuristics, relationships and symbolic models), their limited “naturalness” of human-machine interactions, the demonstration (or lack thereof) of ‘common sense’ reasoning, and their limited capacity to learn by analogy (Feigenbaum et al., 1989). The knowledge transfer, acquisition, or elicitation process itself has also presented issues for designers of expert systems as people are not always able to give complete or accurate reports of their mental processes (Nisbett & Wilson, 1977), nor are these reports purely objective descriptions of these processes (White, 1988). Thus, the endeavour of expert systems engineering is often seen more as art than science (Feigenbaum, 1977):

Art: “the principles or methods governing any craft or branch of learning.” Art: “skilled workmanship, execution, or agency.” These the dictionary teaches us. (Donald) Knuth tells us that the endeavour of computer programming is an art, in just these ways. The art of constructing intelligent agents is both part of and an extension of the programming art. It is the art of building complex computer programs that represent and reason with knowledge of the world. Our art therefore lives in symbiosis with the other worldly arts, whose practitioners – experts of their art – hold the knowledge we

need to construct intelligent agents. In most “crafts or branches of learning” what we call “expertise” is the essence of the art. And for the domains of knowledge that we touch with our art, it is the “rules of expertise” or the rules of “good judgement” of the expert practitioners of that domain that we seek to transfer to our programs.” (p. 3)

### **3.4 Knowledge Representation and Quantum Computers – A New Hope**

Minsky’s (2006) discussion on multiple ways of representing knowledge is instructive (see p. 280-297). An incident can be naturally represented with a story or script. Items named in a story or script can refer to more complex structures in a collection of symbols (i.e., semantic network), and such connecting links are very versatile as each connection-link can refer to another type of representation. Pairs of semantic networks can also represent the effects of actions and can co-evolve over time (in a similar sense to storied spaces) wherein agents respond, adapt, and contribute to their meaning over time and in different contexts (Baskin, 2008). Minsky uses the term Trans-Frame (p. 283) to name a pair of representations of the conditions before and after an action was conducted. Linking Trans-Frames allows the formation of a story or narrative and can also include information on common sense matters that provide answers to the following questions (p. 284): Who performed the action, and why? Where and when did the action begin and end? Was it intentional or not? What purpose did it intend to serve? What kinds of methods or instruments were used? What obstacles were overcome? What were its other side effects? Which resources did it engage? What was expected to happen next? Default assumptions allow rapid access to common sense knowledge via activation of a frame. Minsky also derived the idea of a structure that can produce records of what you are doing at a certain moment – a so called K-line – which is a snapshot of a mental state that when later activated will put you into a similar state (see also Minsky 1988):

You want to repair a bicycle. Before you start, smear your hands with red paint. Then every tool you need to use will end up with red marks on it. When you’re done, just remember that red means ‘good for fixing bicycles.’ Next time you fix a bicycle, you can save time by taking out all the red-marked tools in advance. If you use different colors for different jobs, some tools will end up marked with several colors. That is, each agent can become attached to many different K-lines. Later, when there’s a job to do, just activate the proper K-line for that kind of job, and all the tools used in the past for similar jobs will automatically become available” (suggestion by Kenneth Haase who was a student of Minsky, see Minsky 1988, p. 82).

Ultimately, it is a combination of these representations that could provide the most complete and flexible forms of knowledge representation and problem solving (Minsky, 2006). In learning, humans often perform metaphorical extensions of new knowledge structures based on pre-existing knowledge (Carroll & Thomas, 1982) by way of learning by analogy. Similarly, experts often draw upon case studies and examples in their approach to solving complex problems (Hinsley et al., 1977) and later, in explaining their methods and reasoning. With this sort of flexibility and tolerance for the elaboration of existing concepts comes the ability to take into account new information, understand novel phenomena, and adapt knowledge (and hence, responses) in light of changing circumstances (McCarthy, 1998).

A quantum computing approach could further bolster the flexibility of such an approach to knowledge representation and adaptation in situations where this is considerable uncertainty (Yukalov et al., 2018), when order and context influence perception and decision making in non-insignificant ways, or when ‘distinct’ knowledge silos appear to exhibit some extreme dependencies (Pothos & Busemeyer, 2013). In addition, a quantum computer’s ability to search problem spaces of high dimensionality more efficiently than classical computers will enable the development of more general and far-reaching knowledge structures without having to compromise on the depth of specialist knowledge areas.

#### **4 Examples of Practical Applications**

Quantum computing allows us to rethink what we can learn from expert systems. It is no coincidence that quantum computing is regarded as a promising tool for making better products at lower costs in less time; for example, in the chemical industry, it allows modelling of molecules (e.g., molecules with heavy atoms), proteins, polymers, and – in particular – solids at a much higher level of precision and intensity, reducing time consuming feedback approaches such as trial-and-error experiments (Budde & Volz, 2019). Quantum machine learning techniques have also improved classical machine learning algorithms by reducing the time required to train a machine, while providing a richer framework for deep learning (Wilson, 2020). As Hickey (2016) points out, “[a]s computer hardware technology continues to improve (e.g., supercomputing, quantum computing) the trade-off between efficiency and thoroughness will move far toward thoroughness” (p. 94).

In the next three sub-sections we introduce areas we anticipate will benefit from the applicability of quantum concepts. We do not suggest specific methods or step-by-step plans



for doing so; such an inventory was never our intention. Rather, we aim to highlight areas of investigation which sit outside the usual and commonly referenced areas for quantum applications.

#### **4.1 Scientific Discovery and Breakthrough Thinking**

If there are reasons behind discoveries based on study, practice, and principles of information-processing, the question is whether quantum computing can help make discoveries. As with expert systems, heuristics can be designed to simulate or facilitate such a discovery process. Langley et al. (1987) provide insights into how the method of heuristic selective search based on available knowledge of human methods of problem solving can contribute to nontrivial scientific discoveries. According to the authors, “[s]cience imitates life more closely than has been admitted. As with the rest of life, uncertainty is intrinsic to it, and every situation may be viewed from multiple perspectives” (p. 17). Quantum computing may help to provide these multiple perspectives, particularly in those cases where the seeking and searching is less defined, or the problems are not well structured, and their problem-space is wide and complicated. It may also contribute to decomposition of complex problems into sets of problems, then recombining them while selectively applying a set of goals in a way that is hard to achieve via the human mind alone. The ability to test a great number of possible recombinations can provide the foundation for new advances. Technological innovation, for example, often arises as a novel combination of well-known building blocks (Holland, 1995).

Quantum computing allows creation of various knowledge representations and searching selectively with different heuristics through threes of situations; similar to conducting a lot of experiments or simulations in a counterfactual matter. Expert systems can guide the knowledge required for dealing with problem situations and the steps needed to act in the possibility sets. It allows flexibility as task domains can narrow down the heuristics, making them less flexible in deriving new solutions. As we have no idea or guarantee about the success of a specific heuristic, testing several at the same time in “parallel” worlds may help to increase the chances of a (new) solution in a similar computational time (Ablayev & Vasiliev, 2011). It also allows us to test how the processing of different facts can lead to different quantified general insights and enable more explainable and comprehensible AI decisions after the fact (Byrne, 2019). In other words, it can test the implications of various starting points or initial conditions. Parallelism also helps to remind us that this is a normal part of the evolution and path-dependency of single strategies. For example, Richard Lenski’s experiment on E.coli began in

1988 when a single genetically identical clone of E.coli was used to create 12 populations that never mixed; in 2010 the experiment celebrated the milestone of 50,000 generations (around 70,000 now) (for a detailed discussion, see Wilson 2019). Every 75 days (500 generations), mixed-population samples are frozen and stored away<sup>5</sup>, which allows restarting the experiment from that point. By taking a hybrid quantum-classical computing approach, at least in the near-medium term, we can achieve a similar ‘stop-start’ simulation by leveraging the robustness of classical computers with the computational efficiency of quantum computers (Endo et al., 2020).

As there are various problem spaces that represent the initial states (problem, goal etc.), a quantum computing approach could help to understand the implications of such spaces and inform how boundary conditions fed into the system as inputs can affect the outcome of a system. It could help with understanding a variety of synergies (see Corning 2003, p. 17-33) such as synergies of scale (adding more of the same), threshold effects (critical point is reached that leads to an abrupt change of state), or phase transitions, Gestalt effects (synergistic effects that arise from patterns among different parts, their form and structure), functional complementarities (different properties or capacities that join forces to give a new functional characteristic), emergent phenomena, augmentation or facilitation (combined effects that enhance a dynamic process), or convergent effects.

However, it is less clear how intuition, creativity, or imagination can emerge from those processes. If – in the spirit of Plato – learning is the acquisition of knowledge and therefore a process of recollection, then computational tools can be extremely powerful in faster acquisition and application of knowledge. Scientists, in general, come upon truly fruitful ideas only very rarely and are typically more concerned with ‘normal science’ (Kuhn, 2012) rather than novel approaches which face “higher level[s] of uncertainty and potential resistance by incumbent paradigms” (p. 1363)(Veugelers & Wang, 2019). Novel research after all, is an uncertain business; novel papers experience higher variance in citation performance, delayed recognition, and are typically published in journals with lower Impact Factors (Wang et al., 2017). A computational system, however, can be trained to think analogically and not concern itself with the (perceived) uncertainty that can constrain novelty in research. It should be faster than humans to recognize dissimilarities side-by-side with similarities. Thus, powerful computer systems can derive innovative and productive new ideas, and may even provide us

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<sup>5</sup> <http://myxo.css.msu.edu/ecoli/overview.html>

with an understanding of the process of creative thinking. Its pattern recognition abilities are better than those of humans, and such a process of identification and recognition can help in the discovery process. As invention and discoveries have something of the nature of the unpredictable (Yukawa, 1974), finding ways of identifying, increasing the possibility, or of amplifying the probability of innovations via counterfactual simulations may help creativity to show itself in a more structured way. Simulations are able to cope with failures, and experiencing repeated failures is often a source of future success through learning. In addition, using many counterfactuals can help deal with an abundance of information and the bewildering array of new stimuli that can create barriers to human creativity. Hence, a quantum approach can also help solve problems of information overload (Logesh et al., 2018). As a fixed framework is not able to cope with such an excessive amount of information, new avenues of creativity can emerge. Allowing for simultaneous pathways provides the tenacity to keep going until a ray of light is found in the darkness; enabling expansion by using different pathways, so that little by little the darkness is gradually dispelled. Mapping the implications of simultaneous pathways also considers that the discoveries are part of multilayered reality in our social world where history matters.

## 4.2 Complex Systems

Complex systems represent a fascinating context for the implementation of quantum computing, as simulation of complexity requires an enormous amount of computational power. Andrew Shipolov, a Professor of Strategy at INSEAD noted in a blog that quantum computing is “best suited for cases that involve massive data processing, but don’t require 100 percent precision in computations”<sup>6</sup>. Quantum computing will facilitate advancement of fields in the area of cybernetics, nonlinear science, and systems theory, and have produced myriad models of complex behaviour (see e.g., Holland, 1995, Mitchell, 2009, Page, 2010, Miller and Page 2009 for an overview) by providing better ways of exploring challenging aspects such as feedback loops (Serman, 1994), and network theory (Newman, 2010), which builds a theoretical and algorithmic frame applicable to many settings (Barabási, 2012). It can also possibly help to identify and describe regularities in a system. As Axelrod and Cohen (2000) note, “[s]ocial systems exhibit dynamic patterns analogous to physical, biological, and computational systems” (p. 21). Quantum computing will provide new ways of looking at agent-based models, seeing society as a computational device (Epstein, 2006); endowing

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<sup>6</sup> <https://knowledge.insead.edu/blog/insead-blog/the-real-business-case-for-quantum-computing-10836>

entities (e.g., individuals, objects, technologies etc.) with simple behaviour rules similar to expert systems, and then identifying emergent behaviour patterns in the society to which these agents belong (Epstein & Axtell, 1996). Quantum computing has the power to explore groups, organisations, and societies as if they were organisms or open complex living systems, offering the opportunity to examine the role of information and communication and the contextual forces determining interaction patterns (Axelrod & Cohen, 2000). The concept of complex adaptive systems (Miller & Page, 2009) can then be used to examine the role of information and communication, as well as the contextual forces determining interaction patterns (Axelrod & Cohen, 2000). Quantum computing may help us to better understand how the internal mechanisms of complex systems can result in structured or self-organized states. Parallelism through applying counterfactuals helps in understanding how individuals and systems are able to handle a novel world. Quantum parallelism offers the ability to do so simultaneously with an exponential (as opposed to proportional in the case of classical computers) return to the size of the system (i.e., number of qubits) (Steane & Rieffel, 2000) and hence, the ability to handle larger and more complex problem spaces. It also offers indications of how systems adapt, and therefore how to identify ways of changing a system's performance. As Holland (1995) points out, "[w]hen one hypothesis fails, competing rules are waiting in the wings to be tried" (p. 53). Central to a dynamic system is an analysis of its sensitivity (Epstein, 2006). Small changes in input (micro-specification) can have an effect on the output (macrostructure). The fact that complex emergent patterns are notoriously difficult to identify (Kitto, 2008) and even more difficult to simulate mathematically will require the abilities of quantum computing to derive new insights. Crutchfield (2017) notes that increasingly powerful computers provide an entrée to understanding complicated and unpredictable phenomena with nonlinearly interacting systems. Having better tools to improve the process, storage, and transmission also makes it possible to more rapidly determine the state of the system (Axelrod & Cohen, 2000).

Scalable quantum computers can also be built by networking together many simple processor cells (Nickerson et al., 2013). The realization of a global quantum network could allow improvements in the accuracy of global timekeeping, improved navigation and Earth sensing, and more precise telescopes (Simon, 2017). Insights from computational mechanics integrates ideas from dynamical systems, computational theory, and the theory of statistical inference (Mitchell, 2009) to guide what can be achieved with quantum computing. Chaotic measurement theory, for example, has successfully exploited the intimate relation between information, computation, and forecasting within the framework of statistical and

computational mechanics (Crutchfield & Young, 1989). A key goal (one that is both challenging and ambitious) of the field of computational mechanics is to one day lay out the foundation of a fully automated artificial science where theories are automatically built from raw data, similar to the endeavours of early expert system researchers.

Complex systems such as economies, cities etc. are organic – that is, always discovering, creating, and in process (Arthur, 2009) – thus, knowledge, information, creativity, and insights are key resources in a constantly changing world where possibilities and problems are created as ongoing ecological interactions call for additional responses. In this environment, entities are not always stable and events not always repeatable. Understanding change in such a setting requires comprehension of the dynamic communication and feedback channels within the system, as well as the architecture and design of such systems (Torgler, 2019). Insights from expert systems can be valuable, and complex systems such as smart cities need to integrate elements noted by Rob Kitchin: episteme/scientific knowledge, tech/practical instrumental knowledge with phronesis (which is the knowledge developed from practice and deliberation), and metis (the knowledge derived from experience) (Schechtner 2017, p. 75). For example, insights from quantum mechanics have improved the speed and accuracy of urban trip planning and travel recommendation systems (Logesh et al., 2018), quantum cryptography is poised to enable more secure Internet-of-Things (IoT) in smart cities (Routray et al., 2017), and even improve moving target tracking algorithms deployed in video surveillance, human-computer interaction, and human behaviour analysis (Zhigang et al., 2020).

### **4.3 The Future of Sports**

New technologies of Big Data, AI, and quantum computing have penetrated the sports environment (Torgler, 2020). Technology is becoming a key player both on and off the field in sports arenas, and is currently implemented to improve the performance of athletes, sports consumption, and sports management (Schmidt, 2020). Sports business leaders require an understanding of the role of technology, how technology affects their business today, and how it will affect it in the future (Schmidt, 2020). New opportunities through new technologies and data can challenge and disrupt the sports environment, as evident with the growing importance of data analytics. The analytical method of winning (made famous to a broad audience by Michael Lewis' book *Moneyball*) drew substantial attention despite its broad criticism. Oakland Athletics tried to find new and better ways of valuing baseball players, often discovering value in players who had been discarded or overlooked. Other clubs such as the

Boston Red Sox also successfully implemented the same methods, winning the World Series in 2004, 2007, and 2013. However, after several disappointing seasons, in 2016 they announced their move away from the data-based approach and a return to relying upon the judgement of baseball experts (Lewis, 2016). This may indicate (as suggested in this contribution) that a combination of expert knowledge and technology might not be a bad avenue in sports. Expert knowledge can guide the way information is collected; for example, under Daryl Morey, the Houston Rockets started to collect not just the number of rebounds per player but also the number of genuine opportunities for rebounds (Lewis, 2016). Morey also looked at the predictions made by his staff, realising that they needed scouts to, for example, rate a player's ability to do things they knew were important (e.g., shooting, finishing, getting to the rim, offensive rebounding etc.): "The trick wasn't just to build a better model. It was to listen both to it and to the scouts at the same time. 'You have to figure out what the model is good and bad at, and what humans are good and bad at,' said Morey" (Lewis, 2016, p. 38); for example, models were bad at identifying when a player was not trying hard enough. Expert systems have been used to identify sports talent (Papić et al., 2009) and have also been used in the area of sports biomechanics (Bartlett, 2006). Bartlett concludes by stressing that "[a]utomatic marker-tracking systems allow more, and more accurate, human movement data to be collected. This could lead to the use of fuzzy Expert Systems for diagnosis of faults in sports techniques, a substantial development of the rudimentary Expert Systems currently embedded in some video analysis packages" (p. 478). Going one step further, quantum computing can extend the reach and generalisations of probability-based methods, and greatly increase the computational space (exponentially with the size of the system) available to perform such parallel computations (Steane & Rieffel, 2000).

Digital footprints can improve athletes' performance, long-term health status, and stress resistance; can even prolong their sports career (Passfield & Hopker, 2017), and can feed into how tactics are chosen (Torgler 2020). Instant feedback through, for example, the use of these wearable technologies (Torgler 2019) may transform how matches are organized (Memmert & Rein, 2018), but they require substantial computation power, particularly in highly interactive environments such as team sports. Artificial neural networks (ANNs) and advanced AI technologies may help in the sports environment due to their capacity of dealing with complex input-output relations (Torgler 2020). They can be used for various purposes, for example: identify game strategies; identify patterns among players and teams; predict outcomes and risks; allow for tactical analysis; predict injuries or training loads; or identify talents (Casals &

Finch, 2017; Chase, 2020; Kahn, 2003; McCullagh & Whitfort, 2013; Pena & Touchette, 2012; Rygula, 2003). Quantum computation and information systems provide an opportunity to handle the complexity and rich data of sports ecosystems, offering new ways of analysing sports-related data (Torgler 2020). For example, camera-based player tracking systems capture every player's position for every NBA game at 25 frames per second (Chase, 2020). Quantum computing can be particularly powerful in identifying and 'playing out' counterfactual "what if" scenarios during a game, therefore revolutionising real-time game strategies by quickly understanding the implication of these "what if" situations.

## **5 Conclusions**

In this contribution, we have highlighted the potential for quantum theories to reignite the art and science of expert systems and knowledge engineering. With their fundamental grounding in uncertainty, quantum concepts are able to expand theoretical and practical boundaries of research and exploration. We have demonstrated similarities between quantum concepts and expert knowledge, identified quantum advantages as well as limitations, and outlined three practical domains we regard as largely unexplored in popular accounts of quantum theory and contain highly fruitful applications of quantum technologies.

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## References

- Ablayev, F., & Vasiliev, A. (2011). Classical and quantum parallelism in the quantum fingerprinting method. International Conference on Parallel Computing Technologies,
- Aerts, D., & Czachor, M. (2004). Quantum aspects of semantic analysis and symbolic artificial intelligence. *Journal of Physics A: Mathematical and General*, 37(12), L123.
- Ambainis, A. (2004). Quantum search algorithms. *ACM SIGACT News*, 35(2), 22-35.
- Antonio, A., & Lluís, M. (2016). Certified randomness in quantum physics. *Nature*, 540(7632), 213. <https://doi.org/10.1038/nature20119>
- Arthur, W. B. (2009). *The nature of technology: What it is and how it evolves*. Simon and Schuster.
- Ashtiani, M., & Azgomi, M. A. (2015, 2015/05/01/). A survey of quantum-like approaches to decision making and cognition. *Mathematical Social Sciences*, 75, 49-80. <https://doi.org/https://doi.org/10.1016/j.mathsocsci.2015.02.004>
- Atmanspacher, H. (2004). Quantum approaches to consciousness.
- Axelrod, R., & Cohen, M. (2000). *Harnessing Complexity Organizational Implications of a Scientific Frontier* Free Press.
- Baaquie, B. E. (2013). *The theoretical foundations of quantum mechanics*. Springer Science & Business Media.
- Banks, T. (2019). Quantum mechanics : an introduction. <http://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&db=nlabk&AN=1897033>
- Barabási, A.-L. (2012). The network takeover. *Nature Physics*, 8(1), 14-16.
- Bartlett, R. (2006). Artificial intelligence in sports biomechanics: New dawn or false hope? *Journal of sports science & medicine*, 5(4), 474.
- Barz, S., Kashefi, E., Broadbent, A., Fitzsimons, J. F., Zeilinger, A., & Walther, P. (2012). Demonstration of blind quantum computing. *Science*, 335(6066), 303-308.
- Baskin, K. (2008). Storied Spaces: The Human Equivalent of Complex Adaptive Systems. *Emergence : Complexity and Organization*, 10(2), 1-12.

- Bennett, C. H., Brassard, G., Crépeau, C., Jozsa, R., Peres, A., & Wootters, W. K. (1993). Teleporting an unknown quantum state via dual classical and Einstein-Podolsky-Rosen channels. *Physical Review Letters*, 70(13), 1895.
- Bennett, C. H., & Shor, P. W. (1998). Quantum information theory. *IEEE transactions on information theory*, 44(6), 2724-2742.
- Born, M. (1926). Quantenmechanik der stoßvorgänge. *Zeitschrift für Physik*, 38(11-12), 803-827.
- Brassard, G., Hoyer, P., & Tapp, A. (1998). Quantum Counting. *arXiv.org*. <https://doi.org/10.1007/BFb0055105>
- Budde, F., & Volz, D. (2019). *The next big thing? Quantum computing's potential impact on chemicals*.
- Bussemeyer, J. R., & Bruza, P. D. (2012). *Quantum models of cognition and decision*. Cambridge University Press.
- Byrne, R. (2019). Counterfactuals in Explainable Artificial Intelligence (XAI): Evidence from Human Reasoning. IJCAI,
- Carroll, J. M., & Thomas, J. C. (1982). Metaphor and the cognitive representation of computing systems. *IEEE Transactions on systems, Man, and Cybernetics*, 12(2), 107-116.
- Casals, M., & Finch, C. F. (2017). Sports Biostatistician: a critical member of all sports science and medicine teams for injury prevention. *Injury prevention*, 23(6), 423-427.
- Chase, C. (2020). The Data Revolution: Cloud Computing, Artificial Intelligence, and Machine Learning in the Future of Sports. In *21st Century Sports* (pp. 175-189). Springer.
- Corning, P. (2003). *Nature's magic: Synergy in evolution and the fate of humankind*. Cambridge University Press.
- Crutchfield, J. P. (2017). The origins of computational mechanics: A brief intellectual history and several clarifications. *arXiv preprint arXiv:1710.06832*.
- Crutchfield, J. P., & Young, K. (1989). Inferring statistical complexity. *Physical Review Letters*, 63(2), 105.
- Deutsch, D. (1989). Quantum Computational Networks. *Proceedings of the Royal Society of London. Series A, Mathematical and Physical Sciences*, 425(1868), 73-90.

- Deutsch, D., & Jozsa, R. (1992). Rapid solution of problems by quantum computation. *Proceedings of the Royal Society of London. Series A: Mathematical and Physical Sciences*, 439(1907), 553-558.
- Dunjko, V., & Briegel, H. J. (2018). Machine learning & artificial intelligence in the quantum domain: a review of recent progress. *Reports on Progress in Physics*, 81(7), 074001.
- Endo, S., Cai, Z., Benjamin, S. C., & Yuan, X. (2020). Hybrid quantum-classical algorithms and quantum error mitigation. *arXiv preprint arXiv:2011.01382*.
- Englert, B.-G. (2013). On quantum theory. *The European Physical Journal D*, 67(11), 1-16. <https://doi.org/10.1140/epjd/e2013-40486-5>
- Epstein, J. M. (2006). *Generative social science: Studies in agent-based computational modeling* (Vol. 13). Princeton University Press.
- Epstein, J. M., & Axtell, R. (1996). *Growing artificial societies: social science from the bottom up*. Brookings Institution Press.
- Feigenbaum, E. A. (1968). *Artificial intelligence: themes in the second decade*.
- Feigenbaum, E. A. (1977). *The art of artificial intelligence. 1. Themes and case studies of knowledge engineering*.
- Feigenbaum, E. A., McCorduck, P., & Nii, H. P. (1989). *The Rise of the Expert Company; How Visionary Companies Are Using Artificial Intelligence to*. Vintage Books.
- Feynman, R. P. (1982). Simulating physics with computers. *Int. J. Theor. Phys*, 21(6/7).
- Galindo, A., & Martin-Delgado, M. (2001). Information and Computation: Classical and Quantum Aspects. *arXiv.org*, 74(2). <https://doi.org/10.1103/RevModPhys.74.347>
- Grover, L. K. (1996). A fast quantum mechanical algorithm for database search.
- Haag, R. (2013). On the sharpness of localization of individual events in space and time. *Foundations of Physics*, 43(11), 1295-1313.
- Harrow, A., Hassidim, A., & Lloyd, S. (2009). Quantum algorithm for solving linear systems of equations. *arXiv.org*, 103(15). <https://doi.org/10.1103/PhysRevLett.103.150502>

- Heisenberg, W. (1962). *Physics and philosophy. The revolution in modern science, 1958*. Harper & Row Publishers, New York.
- Hickey, T. J. (2016). *Twentieth-Century Philosophy of Science: A History*. Thomas J. Hickey. [https://books.google.com.au/books?id=L\\_y-CwAAQBAJ](https://books.google.com.au/books?id=L_y-CwAAQBAJ)
- Hinsley, D. A., Hayes, J. R., & Simon, H. A. (1977). From words to equations: Meaning and representation in algebra word problems. *Cognitive processes in comprehension*, 329.
- Holland, J. H. (1995). *Hidden orderhow adaptation builds complexity*.
- Kahn, J. (2003). Neural network prediction of NFL football games. *World Wide Web electronic publication*, 9-15.
- Khrennikov, A. (2015). Quantum-like modeling of cognition. *Frontiers in Physics*, 3, 77.
- Kimble, H. J. (2008). The quantum internet. *Nature*, 453(7198), 1023-1030.
- Kitto, K. (2008). High end complexity. *International journal of general systems*, 37(6), 689-714.
- Kolawole, M. O. (2020). *Electronics : from classical to quantum* (First edition. ed.). CRC Press.
- Krithika, S. (2017). Quantum Key Distribution (QKD): A Review on Technology, Recent Developments and Future Prospects. *Research Journal of Engineering and Technology*, 8(3), 291-294. <https://doi.org/10.5958/2321-581X.2017.00049.6>
- Kuhn, T. S. (2012). *The structure of scientific revolutions*. University of Chicago press.
- Landauer, R. (1996, 1996/07/15/). The physical nature of information. *Physics Letters A*, 217(4), 188-193. [https://doi.org/https://doi.org/10.1016/0375-9601\(96\)00453-7](https://doi.org/https://doi.org/10.1016/0375-9601(96)00453-7)
- Landauer, R. (1999). Information is a physical entity. *Physica A*, 263(1-4), 63-67. [https://doi.org/10.1016/S0378-4371\(98\)00513-5](https://doi.org/10.1016/S0378-4371(98)00513-5)
- Langley, P., Simon, H. A., Bradshaw, G. L., & Zytkow, J. M. (1987). *Scientific discovery: Computational explorations of the creative processes*. MIT press.
- Lewis, M. (2016). *The undoing project: A friendship that changed the world*. Penguin UK.

- Li, J., Yang, X., Peng, X., & Sun, C.-P. (2017). Hybrid quantum-classical approach to quantum optimal control. *Physical Review Letters*, *118*(15), 150503.
- Lindsay, R. K., Buchanan, B. G., Feigenbaum, E. A., & Lederberg, J. (1993). DENDRAL: a case study of the first expert system for scientific hypothesis formation. *Artificial intelligence*, *61*(2), 209-261.
- Lloyd, S. (1995). Almost any quantum logic gate is universal. *Physical Review Letters*, *75*(2), 346.
- Logesh, R., Subramaniaswamy, V., Vijayakumar, V., Gao, X.-Z., & Indragandhi, V. (2018). A hybrid quantum-induced swarm intelligence clustering for the urban trip recommendation in smart city. *Future Generation Computer Systems*, *83*, 653-673.
- McCarthy, J. (1998). Elaboration tolerance. *Common Sense*,
- McCorduck, P. (2019). *This Could be Important: My Life and Times with the Artificial Intelligentsia*. Lulu. com.
- McCullagh, J., & Whitfort, T. (2013). An investigation into the application of Artificial Neural Networks to the prediction of injuries in sport. *International Journal of Sport and Health Sciences*, *7*(7), 356-360.
- Memmert, D., & Rein, R. (2018). Match analysis, big data and tactics: current trends in elite soccer. *German Journal of Sports Medicine/Deutsche Zeitschrift für Sportmedizin*, *69*(3).
- Miller, J. H., & Page, S. E. (2009). *Complex adaptive systems: An introduction to computational models of social life*. Princeton university press.
- Minsky, M. (2006). *The emotion machine : commonsense thinking, artificial intelligence, and the future of the human mind*. Simon & Schuster.
- Mirowski, P. (1990). From Mandelbrot to Chaos in Economic Theory. *Southern Economic Journal*, *57*(2), 289-307. <https://doi.org/10.2307/1060611>
- Mitchell, M. (2009). *Complexity: A guided tour*. Oxford University Press.
- Montanaro, A. (2015). Quantum speedup of Monte Carlo methods. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *471*(2181), 20150301.
- Moret-Bonillo, V. (2018). Emerging technologies in artificial intelligence: quantum rule-based systems. *Progress in Artificial Intelligence*, *7*(2), 155-166.

- Newman, M. E. J. (2010). *Networks an introduction*. Oxford University Press.
- Nickerson, N. H., Li, Y., & Benjamin, S. C. (2013). Topological quantum computing with a very noisy network and local error rates approaching one percent. *Nature communications*, 4(1), 1-5.
- Nilsson, N. J. (2009). *The quest for artificial intelligence*. Cambridge University Press.
- Nisbett, R. E., & Wilson, T. D. (1977). Telling more than we can know: verbal reports on mental processes. *Psychological review*, 84(3), 231.
- Noori, H., & Spanagel, R. (2013). Quantum modeling of common sense. *Behavioral and Brain Sciences*, 36(3), 302. <https://doi.org/10.1017/S0140525X1200307X>
- Orus, R., Muga, S., & Lizaso, E. (2019). Quantum computing for finance: Overview and prospects. *Reviews in Physics*, 4, 100028.
- Otterbach, J., Manenti, R., Alidoust, N., Bestwick, A., Block, M., Bloom, B., Caldwell, S., Didier, N., Fried, E. S., & Hong, S. (2017). Unsupervised machine learning on a hybrid quantum computer. *arXiv preprint arXiv:1712.05771*.
- Page, S. E. (2010). *Diversity and complexity* (Vol. 2). Princeton University Press.
- Papić, V., Rogulj, N., & Pleština, V. (2009). Identification of sport talents using a web-oriented expert system with a fuzzy module. *Expert systems with applications*, 36(5), 8830-8838.
- Passfield, L., & Hopker, J. G. (2017). A mine of information: can sports analytics provide wisdom from your data? *International journal of sports physiology and performance*, 12(7), 851-855.
- Pena, J. L., & Touchette, H. (2012). A network theory analysis of football strategies. *arXiv preprint arXiv:1206.6904*.
- Peres, A. (2002). *Quantum Theory: Concepts and Methods* (1st ed. 2002. ed.). Springer Netherlands. <https://doi.org/10.1007/0-306-47120-5>
- Pothos, E. M., & Busemeyer, J. R. (2013). Can quantum probability provide a new direction for cognitive modeling? *The Behavioral and brain sciences*, 36(3), 255. <https://doi.org/10.1017/S0140525X12001525>

- Resch, S., & Karpuzcu, U. R. (2019). Quantum computing: An overview across the system stack. *arXiv preprint arXiv:1905.07240*.
- Rieffel, E., & Polak, W. (2000). An introduction to quantum computing for non-physicists. *ACM Computing Surveys (CSUR)*, 32(3), 300-335.
- Routray, S. K., Jha, M. K., Sharma, L., Nyamangoudar, R., Javali, A., & Sarkar, S. (2017). Quantum cryptography for iot: Aperspective. 2017 International Conference on IoT and Application (ICIOT),
- Rygula, I. (2003). Artificial neural networks as a tool of modeling of training loads. *IFAC Proceedings Volumes*, 36(15), 531-535.
- Schechtner, K. (2017). Bridging the adoption gap for smart city technologies: an interview with Rob Kitchin. *IEEE Pervasive Computing*, 16(2), 72-75.
- Schmidt, S. L. (2020). How Technologies Impact Sports in the Digital Age. In *21st Century Sports* (pp. 3-14). Springer.
- Schumacher. (1995). Quantum coding. *Physical review. A, Atomic, molecular, and optical physics*, 51(4), 2738. <https://doi.org/10.1103/PhysRevA.51.2738>
- Shannon, C. E. (1948). A mathematical theory of communication. *The Bell system technical journal*, 27(3), 379-423.
- Shor, P. W. (1994). Algorithms for quantum computation: discrete logarithms and factoring. 124-134. <https://doi.org/10.1109/SFCS.1994.365700>
- Shortliffe, E. H., & Rindfleisch, T. C. (2000). Presentation of the Morris F. Collen Award to Joshua Lederberg, PhD. *Journal of the American Medical Informatics Association*, 7(3), 326-332.
- Siler, W. (2005). *Fuzzy expert systems and fuzzy reasoning*. Wiley-Interscience. <https://doi.org/10.1002/0471698504>
- Simon, C. (2017). Towards a global quantum network. *Nature Photonics*, 11(11), 678-680.
- Sriboonchitta, S., Nguyen, H. T., Kosheleva, O., Kreinovich, V., & Nguyen, T. N. (2019). Quantum approach explains the need for expert knowledge: on the example of econometrics. International Conference of the Thailand Econometrics Society,
- Steane, A. M., & Rieffel, E. G. (2000). Beyond bits: The future of quantum information processing. *Computer*, 33(1), 38-45.



- Stehr, N. (2011). *Experts : the knowledge and power of expertise*. Routledge.
- Sterman, J. D. (1994). Learning in and about complex systems. *System dynamics review*, 10(2-3), 291-330.
- Torgler, B. (2019). Opportunities and Challenges of Portable Biological, Social, and Behavioral Sensing Systems for the Social Sciences. In *Biophysical Measurement in Experimental Social Science Research* (pp. 197-224). Elsevier.
- Torgler, B. (2020). Big Data, Artificial Intelligence, and Quantum Computing in Sports. In *21st Century Sports* (pp. 153-173). Springer.
- Trueblood, J. S., & Busemeyer, J. R. (2012). A quantum probability model of causal reasoning. *Frontiers in psychology*, 3, 138-138. <https://doi.org/10.3389/fpsyg.2012.00138>
- Turban, E. (1988). Review of expert systems technology. *IEEE Transactions on Engineering Management*, 35(2), 71-81. <https://doi.org/10.1109/17.6007>
- Tversky, A., & Kahneman, D. (1983). Extensional versus intuitive reasoning: The conjunction fallacy in probability judgment. *Psychological review*, 90(4), 293.
- Veugelers, R., & Wang, J. (2019, 2019/07/01/). Scientific novelty and technological impact. *Research Policy*, 48(6), 1362-1372. <https://doi.org/https://doi.org/10.1016/j.respol.2019.01.019>
- Wang, J., Veugelers, R., & Stephan, P. (2017). Bias against novelty in science: A cautionary tale for users of bibliometric indicators. *Research Policy*, 46(8), 1416-1436.
- White, I. (1988). W (h)ither expert systems?—A view from outside. *AI & SOCIETY*, 2(2), 161-171.
- Wilson, D. S. (2020). *This view of life: Completing the Darwinian revolution*. Vintage.
- Yukalov, V. I., Yukalova, E. P., & Sornette, D. (2018). Information processing by networks of quantum decision makers. *Physica A: Statistical Mechanics and its Applications*, 492, 747-766.
- Yukawa, H. (1974). Creativity and Intuition: A Physicist Looks at East and West. *American Journal of Physics*, 42(5), 431-434. <https://doi.org/10.1119/1.1987732>
- Zhaokai, L., Xiaomei, L., & Nanyang, X. (2014). Experimental realization of quantum artificial intelligence. *arXiv preprint arXiv:1410.1054*.



Zhigang, L., Jin, S., & Xufen, H. (2020). Smart City Moving Target Tracking Algorithm Based on Quantum Genetic and Particle Filter. *Wireless communications and mobile computing*, 2020. <https://doi.org/10.1155/2020/8865298>