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

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Abstract:

In this contribution, we highlight the potential for quantum theories to reignite the art and science of expert systems and knowledge engineering. With their fundamental grounding in uncertainty and unpredictability, quantum concepts are able to expand theoretical and practical boundaries of research and exploration. We demonstrate the similarities between quantum concepts and expert systems, outlining five domains (Scientific Discovery, Creativity and Breakthrough Thinking; Complex Systems; Medical Sciences and Advice; Strategic Business Management; and Future of Sports) we regard as largely unexplored in popular accounts of quantum theory; as such, these are low hanging fruit for the application of quantum technologies.

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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 (when compared to costs associated with employing human experts), increased productive output, improved quality, and consistency in the application of expertise, reduced downtime and reduction of uncertainty in decision-making systems. They also enable greater flexibility, reliability, and responsiveness in day-to-day problem solving activities, and help to capture scarce knowledge (Turban, 1988). Despite the high expectations regarding the use of expert systems across a variety of operational contexts, including production planning, teaching, resource utilisation, climate forecasting, industrial process control and engineering analyses (Shu-Hsien, 2005), such systems are not anymore widely used.

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. Further, many opportunities exist at the intersection between quantum computation, quantum theory, and AI (Ying, 2010).

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 endeavours outside of those usually mentioned in popular press reports of quantum technologies. In the first section, we introduce seminal works in quantum theory, quantum mechanics, quantum information theory, quantum logic, and quantum computation. Next, we question the current relevance of human expertise, reasoning, and decision making in the AI and quantum era. In the following section, we provide five domains that – in our estimation – present fruitful opportunities for the application of quantum concepts in contexts typically requiring human expertise. We then summarise our findings.

2 Quantum Theories

In the classical sciences, systems are assumed to have well defined properties. If all relevant pre-conditions are known and can be recreated, specific outcomes are likely to occur time and time again. In other words, systems and their behaviour are deterministic. Quantum theory on the other hand, accepts the inherent unpredictability of precise outcomes and recognises that randomness is a fundamental concept in many physical and complex systems (Peres, 2002). Placing greater focus on the evidence of irregularity and randomness has ultimately contributed to a deeper understanding in many fields across the hard and soft sciences alike, hinting at the delicate balance and blurring boundaries between order and chaos in everyday life (Mirowski, 1990). The persistence of uncertainty, dependence on initial conditions, and breakdown of determinism each play a central role in "rational" classical mechanics and also contribute to the formulation of statistical and quantum mechanics, a story well told by Prigogine (1980).

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 in space) (Englert, 2013). Rather than precise predictions, a quantum approach provides insights into more imprecise queries similar to those made by experts (Sriboonchitta et al., 2019). Born's rule (1926) provides the link between the mathematical formalisms and observed (measured) phenomena (events) which transpire. The defining features of said events include localisation in time and space, irreversibility, and random realisation (Englert, 2013).

2.1 Quantum Mechanics

Classical mechanics is an approximate theory of nature with its concept of emergent, objectively real objects having no counterparts in the more exact theory (quantum mechanics) which underlies it (Banks, 2019). The major difference between classical and quantum mechanics relates to the claim by quantum mechanics that there is a fundamental dissimilarity between the observed and unobserved state of an entity or object (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, however, there is yet an underlying and fundamental uncertainty and unpredictability in its exact positioning (Baaquie, 2013). Heisenberg (1962) coined the terms potentiality and actuality to describe the indeterminate (unobserved) state and observed (definite) condition of a quantum entity, respectively. Each observation (measurement) transitions a quantum entity from its state of potentiality to one of its many possible and definite observable conditions.

One could quite reasonably question how quantum indeterminacy is different at all from classical randomness. This distinction was first brought to light in Bohr's (1935) response to the Einstein, Podolsky and Rosen's (EPR) (1935) paradox which appeared to challenge the concept of quantum indeterminacy. The EPR paradox suggested that the unobserved state of one of two physically separated photons (in a net spin zero state) could be predicted by measuring the state of the other (i.e., if the z-component of one photon was measured as 'up', the z-component of the other is known to be 'down' even without performing any measurement of its actual state) and thus, it appeared to communicate information at a rate faster than the speed of light (Baaquie, 2013). Bohr's (1935) response to the EPR paradox pointed out that the EPR view was merely an illusion and reflects only what one chooses to measure (i.e., the more one knows about the z-component, the less one knows about the x- and y-components). Hence, classical probability still failed 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 a possible outcome of the measurement process itself (Baaquie, 2013) rather than to some physically real but 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).

2.2 Quantum Information

The physical nature of information, as opposed to a pure abstraction, 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 forms (i.e., a state of zero or one) 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). As such, one qubit can theoretically contain infinite information when compared to a c-bit, 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), and any quantum logic gate with two or more inputs is universal in the sense that copies of said gate can be linked together to produce any desirable logic circuit – 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. The power of quantum algorithms mostly derives from harnessing the benefits of quantum parallelism (Deutsch & Jozsa, 1992) which is itself enabled by superpositions and entanglement (Rieffel & Polak, 2000). Further, entanglement also enables such concepts as teleportation (Bennett et al., 1993), quantum encryption (Barz et al., 2012), quantum internet (Kimble, 2008), and dense coding (Rieffel & Polak, 2000). By leveraging quantum concepts, quantum computers are capable of being exponentially faster than classic computers (including even the most powerful of high performance classical computers) at certain computations 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).

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). Other well-known quantum algorithms offer substantial speed-ups over their classical counterparts including Shor's (1994) algorithm for efficient prime factorisation (a fundamental complexity to many of today's cryptography technologies), quantum counting algorithm (Brassard et al., 1998) for efficient counting of solutions for a given search problem, and the Harrow-Llyod algorithm (Harrow et al., 2009) for linear equations. Further, the 'true' randomness of quantum physics (Antonio & Lluis, 2016) could be used to implement truly random number generators in Monte Carlo methods of simulation (Antonio & Lluis, 2016).

Novel and non-traditional programming techniques, such as quantum error correction codes, will overcome many of the outstanding issues associated with the fragility of maintaining quantum potentiality states and of the decoherence (collapsing) of these states following quantum measurements (Rieffel & Polak, 2000).

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. 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[1]: "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, pp. 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):

> "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).

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

[1] McCorduck remembers Ed Feigenbaum's visit to Carnegie Mellon in the 1970s, and his teasing Al and Herb with the line "Guys, you need to stop fooling around with toy problems" (McCorduck, 2019, p. 181).

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).

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).

Minsky's (2006) discussion on multiple ways of representing knowledge is instructive (see pp. 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).

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 intelligence 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)

4 Examples of Practical Applications

Despite the promising nature of expert systems, many systems to date have either (1) never progressed beyond the prototype stage or (2) are neither widely nor routinely used in the purpose for which they were designed (Pollitzer & Jenkins, 1985). However, 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. By improving our understanding of the complex molecular-level processes involved, and by opening up new avenues of how to develop effective molecular designs and structures before going into the lab, quantum computing reduces 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). Such techniques can, for example, be used for screening molecules to accelerate the discovery process of new material, which is a challenge when the chemical space is very large (Xia & Kais, 2018). 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 five 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. 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. 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[2], which allows restarting the experiment from that point.

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, pp. 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

[2] http://myxo.css.msu.edu/ecoli/overview.html

acquisition and application of knowledge. Scientists, in general, come upon fruitful ideas only very rarely. A computational system can be trained to think analogically. It should be faster than humans to recognize dissimilarities side-by-side with similarities. Thus, powerful computer systems can derive inventive and productive new ideas, and may even provide us 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"[3]. 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 (Sterman, 1994), and network theory (Newman, 2010), which builds a theoretical and algorithmic frame applicable to many settings (Barabási, 2012). It can also

[3] https://knowledge.insead.edu/blog/insead-blog/the-real-business-case-for-quantum-computing-10836

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 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. 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 Medical Sciences and Advice

The replacement of human physicians with AI medical agents is a common theme in science fiction, and rightly so: as health care systems are continually pressed for resources, costs associated with the provision of health care service continue to increase and do not appear to be slowing down. The overall goal of incorporating concepts, tools and techniques inspired and developed by AI researchers is to assist health care professionals by improving their effectiveness, productivity, and consistency (Agah, 2013); hence, enabling more sustainable health care systems now and into the future. Naturally, for developers of expert systems (a member of the 'hard' AI class), the medical domain was an attractive field of practical application and several developed systems achieved measurable successes: MYCIN (Shortliffe, 1974), INTERNIST (Myers & Pople, 1977), PUFF (Kunz et al., 1978), and VM

(Fagan, 1978), to name a few. The major breakthrough of these expert systems, particularly of MYCIN, was their representation of uncertainty in medical decision-making (Pollitzer & Jenkins, 1985) and their ability to somewhat mimic the processes used by medical professionals in dealing with this uncertainty. Concepts such as fuzzy logic, similar in some ways to quantum logic, yet less general in scope (Schmitt et al., 2009), have also proven effective in expert systems applications to overcome the incomplete and vague information often provided by patients (Prihatini & Putra, 2012).

By taking a quantum approach, a revision of medical expert systems may yield more robust and lasting benefits to the medical community. When used in combination, quantum superposition and interference could be used to drive such quantum expert systems towards the most probable diagnosis. Moreover, treatment plans may be based on a large array of medical knowledge, perhaps gathered automatically and continually updated according to findings and insights from prominent and peer-reviewed medical research journals and databases, and with feedback from actual performance outcomes and metrics resulting from their use in real world environments. By leveraging another major strength of AI – the identification of patterns and trends present in large, multi-dimensional datasets – diagnoses and treatment plans could be derived from complex medical datasets in a much more consistent, accurate and timely manner compared with any possible human counterpart (Naylor, 2018).

Quantum concepts have also been used to study the evolution of epidemics, extending the conventional Susceptible-Infected (SI) and Susceptible-Infected-Susceptible (SIS) models (León & Pozo, 2007). Under this approach, an individual (prior to measurement/testing) exists in some superposition of the two classical states of susceptible and infected, and the quantum model shows a reasonable degree of correlation with actual data collected. One could sensibly extend the use of quantum algorithms to infectious disease surveillance systems wherein experts manage outbreak identification and confirmation by validating (or invalidating) an alarm and if required, initiating an alert and establishing appropriate countermeasures (Texier et al., 2017). Fuzzy methods have again proven effective in their description of data from disease surveillance (Zhang et al., 2016), suggesting that perhaps incorporating quantum concepts will yield additional benefits.

4.4 Strategic Business Management

Decision making in business implies actions based on imperfect information, arising from many dimensions such as social range, genesis (e.g., routine, unanticipated, etc.), scope, differences in the process of decision-makings, consequences, and context (Smelser and Reed 2012). Needless to say, we are currently facing possibly the biggest social and economic crisis that ever hit our planet. However, even before COVID-19, the compounding interactions of rapid technological change, growing economic interdependence, and mounting political instability had rendered the future increasingly murky. Researchers developed elaborate acronyms such as VUCA to describe our volatile, uncertain, complex, and ambiguous world. Unpredictability was already omnipresent – and then the pandemic hit. The crux is that now, in disruptive times, interpolation of historical data no longer allows predicting the future. Many more current context factors need to be incorporated into forecasting models to meet the complex and rapidly changing environmental conditions. As our world could change even more radically in the coming decades than in the past hundred years, quantitative forecasts are becoming increasingly complex and demanding. In just a few decades, a new world will have emerged – our great-grandchildren will not be able to even imagine the world as we know it today (Schmidt & Stoneham, 2020). Using quantum computers could help provide better predictive models and therefore a better database for strategic discussions, thereby improving a company's corporate intelligence. We all want to better understand the new age we are entering, and we need an antenna for what is coming and where we might go. The future is coming fast and will not wait for us. We are on the edge of a dramatically different world brought about by technology that will push the boundaries of what is possible, building a different future. To reap the rewards of progress in quantum computing, we need to find ways to race with the emerging technology.

The desire to predict the future is part of human nature, and we find many examples of this throughout history. Forecasting is the process of making predictions about the future based on historical and current data – most often using trend, indicator, and impact forecasts. Nevertheless, predicting the future is a complex task. Quantitative forecasting models are usually applied to short or medium-term future scenarios and are used to predict future data depending on data from the past. They are suitable when sufficient historical data are available and when some of the patterns in the data are likely to continue (Schmidt, 2020). Managers could use quantum computers to analyse the enormous amount of data they collect about their business ecosystem. Because of their qubits and exponentially larger process memory, quantum computers can simultaneously explore a massive number of future paths, giving them the potential to be so much faster than today's computers. This may generate a better understanding when studying the strengths and limitations of different organizations. As

Drucker (2007) has pointed out, “[j]ust as there are a great number of different structures for biological organizations, so there are a number of organizations for the social organism that is the modern institution. Instead of searching for the right organization, management needs to learn to look for, to develop, to test” (pp. 16-17).

However, quantum computers do not deliver one clear answer. Instead, they provide a narrowed range of possible answers; as such, quantum computers sound less precise than classical computers that offer a single answer. When calculations are limited in scope, quantum computers are indeed less precise, which is one reason they will not replace today’s systems. Instead, quantum computers will be used for different kinds of future scenarios – incredibly complex ones – in which eliminating an enormous range of possibilities will save an enormous amount of time (Ménard et al., 2020). Moreover, the information provided can move the inquiry beyond a narrowly focused operating organization towards exploring opportunities such as whether or not diversification would be helpful. Information systems can then be stronger in evaluating not only inside information but also outside information.

4.5 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).

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 counterfactual "what if" scenarios during a game, therefore revolutionising real-time game strategies by quickly understanding the implication of "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 and unpredictability, quantum concepts are able to expand theoretical and practical boundaries of research and exploration. We have demonstrated the similarities between quantum concepts and expert systems, outlining five domains we regard as largely unexplored in popular accounts of quantum theory and containing highly fruitful applications of quantum technologies.

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No potential conflict of interest was reported by the author(s).

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