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Review

The Individual and the Organizational Model of Quantum Decision-Making and Learning: An Introduction and the Application of the Quadruple Loop Learning

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Abstract: The new Post Accelerating Data and Knowledge Online Society, or '*Padkos*', requires a new model of decision-making. This introductory paper proposes a model where decision making and learning are a single symbiotic process, incorporating man and machine, as well as the AADD (*ánthrōpos, apparatus, decider, doctrina*) amalgamated diamond model of individual and organizational decision-making and learning processes. The learning is incorporated by using a newly proposed quadruple loop learning model. This model allows for controlled changes of identity, the process of creating and the sense-making of new mental models, assumptions, and reflections. The model also incorporates the recently proposed model of quantum decision making, where time collapse of the opted past and the anticipated future (explicitly including its time horizon) into the present plays a key role in the process, leveraging decision making and learning by human as well as artificial intelligence (AI) and machine learning (ML) algorithms.

Keywords: model of quantum decision-making and learning (MQDM&L); AADD diamond model; decision-making and learning; quadruple loop learning; *Padkos*

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1. Introduction

A number of insights from emerging trends, which build on new scientific and technological developments, suggest that a new model of decision-making (DM) and learning might be needed. Several developments and their impact on decision-making and learning (DM&L) are introduced below, three of which will be discussed more fully in this paper: (1) discontinuous change-continuous technological revolutions; (2) artificial intelligence (AI), machine learning (ML), big data; and (3) neuroscience.

Today, both individuals and organizations are faced with discontinuous change of titanic scope and magnitude. The continuously accelerating technological revolution (see *Padkos* at Russ [1]), requiring increasingly faster responses in a new, uncertain, ambiguous and/or unknowable context, and continuous, lifelong learning, necessitates the amalgamation of decision making and the learning process into a single, symbiotic, and synchronized process. This context is forcing the decision maker/learner into making decisions that are new and not necessarily supported by, or directly related to, the past or their past decisions. The decision maker/learner must place less trust in their intuition (system 1, fast thinking, in Kahneman [2]) and their traditional heuristics, which forces them into a slow-thinking mode (System 2 in Kahneman [2]) while thinking itself is being pushed to an increasingly faster pace, and as such will have to be supported by big data and ML (or actually conducted by ML).

The nature of the decision-making and learning (DM&L) process in organizations is also changing due to the infiltration of AI/ML into the DM&L process (see, for example, [3]). Some even suggest that AI-driven decision-making algorithms might be at the core of the digital operating model of the firm of the future that will revolutionize the landscape of business in the 21st century [4]. This results from an automation of decision-making (replacing humans) while increasing the rate of return on scale, scope, and investment in learning [4] (p. 53). Notwithstanding, it can be assumed that more and more decisions will be made by the AI algorithms and platforms, and supported by big data [5,6], both horizontally and vertically (context specific; see a review at [7]).

The harnessing of big data by deep and machine learning (supported by data science, e.g., [8]) is creating a new context for DM&L, since in many cases it is ML (or deep learning) + big data that make the decision (or a recommendation), both for the individual and for the organization. Such data-driven decision-making processes have numerous advantages (e.g., [9]). For example, 'smart' homes, cars, and workspaces will become a reality in the very near future for more and more individuals, while 'smart' manufacturing and office space (collaboration of robots and people) are already a reality for manufacturing and service companies as well as those that have a supplier or buyer relationship with a 'smart' supplier or customer (see example in [10]). This is another factor to consider when discussing individual and/or organizational DM&L processes.

Moreover, today, more is known, based on studies in neuroscience, about individuals' decision-making and learning than ever before, and as elsewhere, such knowledge is accumulating at an exponential rate. For example, it was documented that our brains make decisions approximately 7 s before the conscious mind recognizes that it made a decision (Ref. [11], and review example in [12]). Additionally, researchers proved that memories can be erased [13] and created [14].

Human body–machine interface studies, including neural rehabilitation (see [15]) and prosthetic limb control (see, e.g., [16]) were followed by proposals for brain–computer interfaces [17] that were recently implemented [18]. Additionally, it is anticipated that human brain–cloud interfaces will be used by futuristic technologies, referred to as "neural-nanorobotics" [19], and early research of direct brain-to-brain communication is currently being conducted [20]. This all points to a changing context for, and new understanding of, human decision-making processes. Neuromarketing is another fruitful area of research with a heavy focus on customer decision-making (see, for example, reviews in [21,22]), also causing major ethical concerns (see more about ethics below).

There are additional indicators that this point in *Homo Sapien* history is a unique inflection point. For example, human activity-driven climate change (e.g., [23]) which causes global warming is making significant parts of the planet uninhabitable and potentially causing flooding of major urban areas around the world (e.g., [24]). Being the first generation of a multi-planetary species [25], and being the first generation to consider the possibility of viewing death as a curable disease [26] are other examples.

For the needs of this paper, three of the developments introduced above will suffice for initiating the discussion: (1) discontinuous change-continuous technological revolutions; (2) artificial intelligence (AI), machine learning (ML), big data; and (3) neuroscience.

This introductory paper has three novel contributions. First, the paper details the nature of the symbiotic relationship between decision-making and learning as one amalgamated process and introduces the AADD (*ánthrōpos, apparatus, decider, doctrina*) diamond model of individual and organizational decision-making and learning processes. Next, the paper introduces the quadruple feedback loop learning model, one that allows an entity to control its identity. Finally, the paper details the combined model of organizational and individual quantum decision-making and learning (MQDM&L).

The remainder of the paper is organized into the following sections: In Section 2, the paper briefly discusses the subject of decision-making. Section 3 introduces the AADD amalgamated diamond model of decision-making and learning. Section 4 elaborates on the quantum metaphor to discuss the collapse of past and future time frames into the present and details the combined quantum decision-making and learning model. Section 5 introduces the novel quadruple loop feedback model. In Section 6, the paper adds ethical and cybersecurity considerations into the model. Finally, the paper closes with brief conclusions in Section 7.

2. Decision-Making (DM)

The academic literature regarding DM, both at the individual and the organization/team unit of analysis, is far-reaching (and beyond the scope of this paper). The literature covers theories of individual DM as framing and reference dependence, behavioral economics, bounded rationality and decision heuristics, among others (see examples and reviews from diverse perspectives in [27–30]). Organizational models of DM include, but are not limited to, rational, administrative, political, stage-based (see interesting review in [31]), sense making and decisions in public organizations [32], ad hoc problem solving, exception management [33], and the garbage can model of decision-making [34]. The brief discussion above about the impact of big data and ML on DM&L now and in the future espouses the author's preference to the garbage can model of DM [34] since it overtly and seamlessly enables the incorporation of data and digital algorithms into the model described herein.

3. The AADD (Ánthrōpos, Apparatus, Decider, Doctrina) Diamond Model

Russ [1] recently described a model whereby decision-making and the learning processes must occur simultaneously due to external pressures and demands (see also [35]) and such a seamless process is enabled by AI machine algorithms (ML, deep learning, etc.) and digital systems infrastructure supported by big data and cloud computing (e.g., [36]). For example, see the McKinsey and Company report on the transformation in health care resulting from the utilization of AI, and the impact it will have on organizations and their workforce [37].

Moreover, the most recent research suggests that data-driven, DM-utilizing analytics allow companies to significantly outperform their competition [38]. Incorporating blockchain technology into this mix will only accelerate and increase the prospects of such technologies to transform businesses and industries [39] as they try to match the needs and challenges resulting from the continuously accelerating technological revolution [1]. Further, Kahneman et al. [40] (pp. 240–241) recently suggested adding a role of 'decision observer', to improve decision-making in a judgment context. This role would enable online, ongoing learning in parallel with team decision-making, and as such, improve the effectiveness of the decision made, consistent with the model proposed here, of bringing learning and decision-making into one single amalgamated process.

All this and more require and enable a new DM&L process (see Figure 1 for the basic diamond description), described below. This model is an attempt to consolidate decision-making and learning into one amalgamated process.

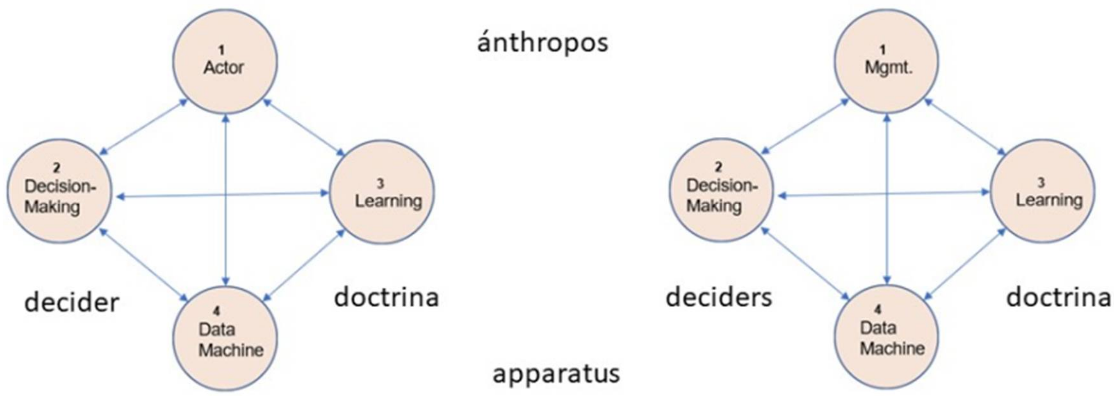

Figure 1. The AADD diamond model of individual and organizational decision-making and learning process. Source: Author's elaboration.

4. The Quantum Metaphor and Maybe More

Gleaning from quantum physics (e.g., [41]), the collapse of the wave function when being monitored by an observer is mostly known through the thought experiment of Schrödinger's cat and the famous question: Is the cat alive or dead, and when? (see recent discussion in [42]). As suggested by Josephson [43], in a biological reality sense, it is the decision made by the observer, to observe, that is causing the collapse of the wave (see [43], Table 1, p. 44). Here, the author will use such a collapse as a metaphor in terms of a time frame collapse (and not probabilities). There might be more than a metaphor here since, based on neural brain studies, there is evidence that memorizing the past is (in some cases) rewriting the memory anew (see [44]) and that the expectations (about the future) of an observer have an impact on the neural level of their perceptions of reality (see [45]). For an observer, at a specific point in time (and space) there is only the present; future and past are the product of their mind (see discussion in [46]).

In this paper, the author will elaborate on the model proposed in Russ [1,47] of quantum decision-making (the organizational/team and the individual) and will also utilize the consolidation of DM and learning into one process (as mentioned above) while adding a quadruple feedback loop learning model to complete this model (see Figures 2 and 3).

For the organizational process (see Figure 2), the alignment of the time horizon as well as the political process of which one of the four specific feedback loop to adopt are probably the most contentious stages since they will frame the issue to be resolved. If the data needed for the use of an AI/ML algorithm is available (which in some cases is an issue, especially regarding 'good' data), this could make such a process more efficient, but not necessarily effective (see more about ML limitations in [48]), since those algorithms do not yet seem to be trained in utilizing the double, triple or quadruple loops. ML algorithms are useful for efficiently dealing with stochastic data. Still, they need a human actor to define for them the issue to solve, including constraints, and to provide data (at least some, for deep learning; and more so for ML). This is not to say that the algorithm questions or inputs cannot cause a human actor to engage in a double-loop learning [49] or even in a higher-level refinement. On a more basic level, having the needed data in the appropriate form for such algorithms and/or for a human decision maker, is far from simplistic. A recent case of pandemic data (or lack of) can vividly illustrate such complexity (see the case described in [50]). Additionally, ML has well publicized issues with racial biases which illustrates another aspect of the framing as discussed here (see, for example, [51]). Moreover, Kahneman et al. [40] (pp. 327–328) suggested at least seven cases/reasons when more data, or more accurate data that can improve the efficiency of the decision-making process, may harm effectiveness (at least for long-term) or even other aspects of efficiency. For example, more data can be extremely expensive and may introduce errors. Additionally, standardization (as a result of more data) may cause social harm (alienation), preventing new norms from being established.

For the individual (see Figure 3), the choice of which feedback loop to pursue will be theoretically easier but getting to the use of the triple or the quadruple loop may cause emotional difficulties. Additionally, access to data might not be simple in many cases. Some new technologies might help here. For example, using virtual reality for human–computer interaction [52] to support gaming and/or scenario planning can be useful in experimenting with new possibilities and enable the individual to test different identities, issues and solutions. Additional stages of validation and confirmation are of course advisable as well as a follow up.

As suggested in Russ [1,47], it is the collapse of a specific future (including a specific time horizon) and a particular past, at a specific point in time, that enables the decision to happen (see also the discussion of time in Myllykoski [53]). Using cognitive psychology as a possible mechanism to activate this time frame collapse, one should consider a change of circumstances, motivation and/or valence of an outcome (using expectance theory-see Renko et al. [54] for example) as a first step. To complement the collapse, an appropriate past is chosen, driven by the need to minimize the cognitive dissonance between the new preferred future and the past, at the present time (e.g., [55]). The plausibility of such a scenario was recently confirmed by studies of brain activity while constructing and evaluating imaginative future scenarios at the neural level. Unique network activity was detected for assessing the valence of the newly imagined future [56].

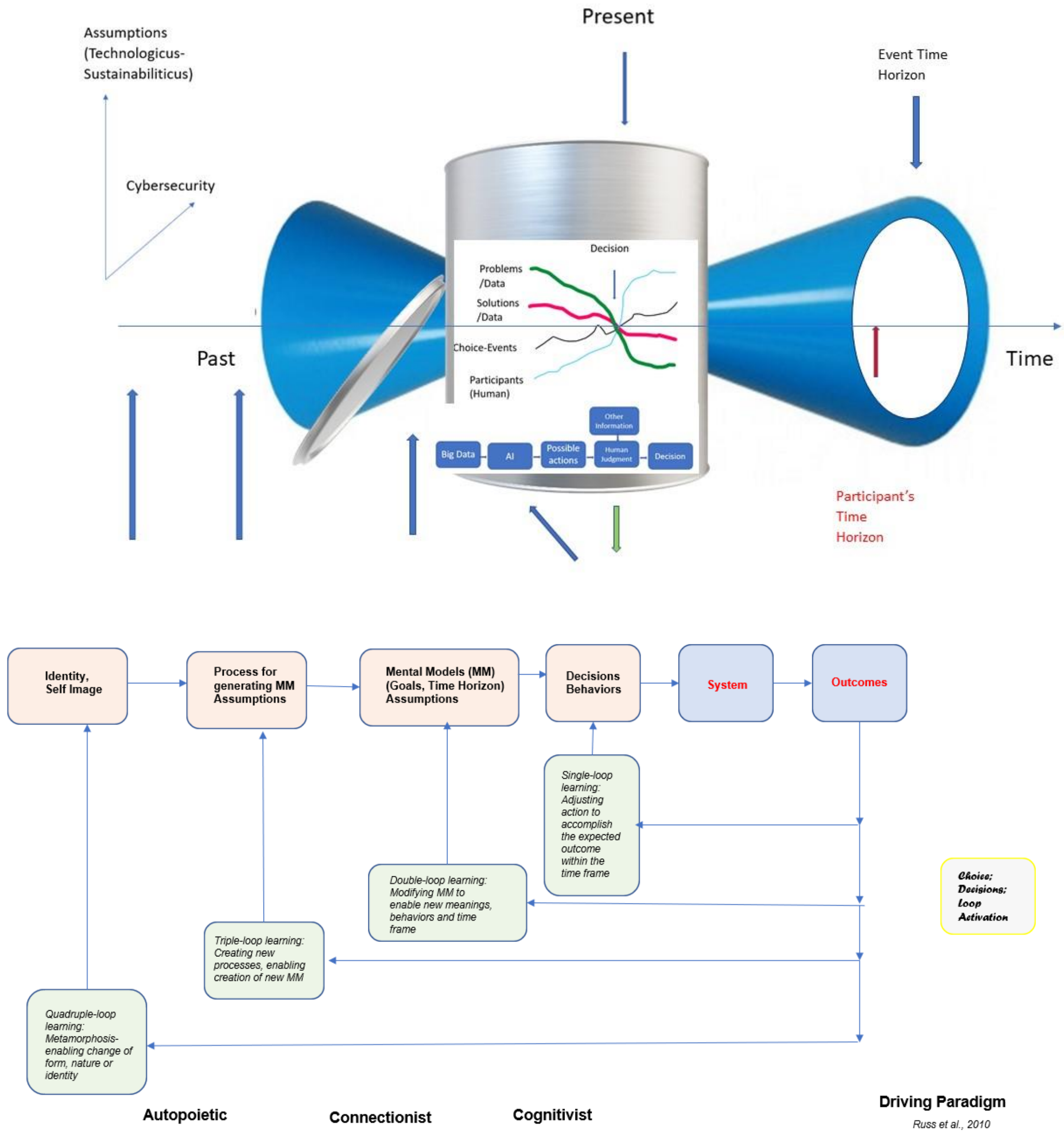

Figure 2. Organizational model of quantum decision-making and learning (MQDM&L). Source: Ref. [1] Russ 2021, Figure 6b (p. 15) and Author's elaboration.

This model differs from other models of quantum decision-making that look at the probabilistic aspects of DM (e.g., [57]). To the best of our knowledge, this is the first such model suggesting the collapse of time frames in managerial literature.

The model (among many other aspects) can explain why change is so difficult and also how change can be accelerated by bringing-in a different past, or a different aspect of the past, into the collapse of time to accommodate the desired future. This model is consistent with the autopoietic paradigm (see Russ et al. [58] elaboration on knowledge and learning) and Luhmann's theory of autopoietic social systems (see discussion in [59]).

The actor (or entity) has a choice of which past to bring forward (consistent with neural studies, as mentioned earlier). This and consciously and rationally activating different modes of feedback (or using different mechanisms; see example in Kross [60]) may cause the actor (or entity) to arrive at a different decision. The same can be said about the future that is brought back to the present. For example, using 'presencing' (and the U theory; see Scharmer [61]) may enable a completely new set of potential futures, and result in a different decision.

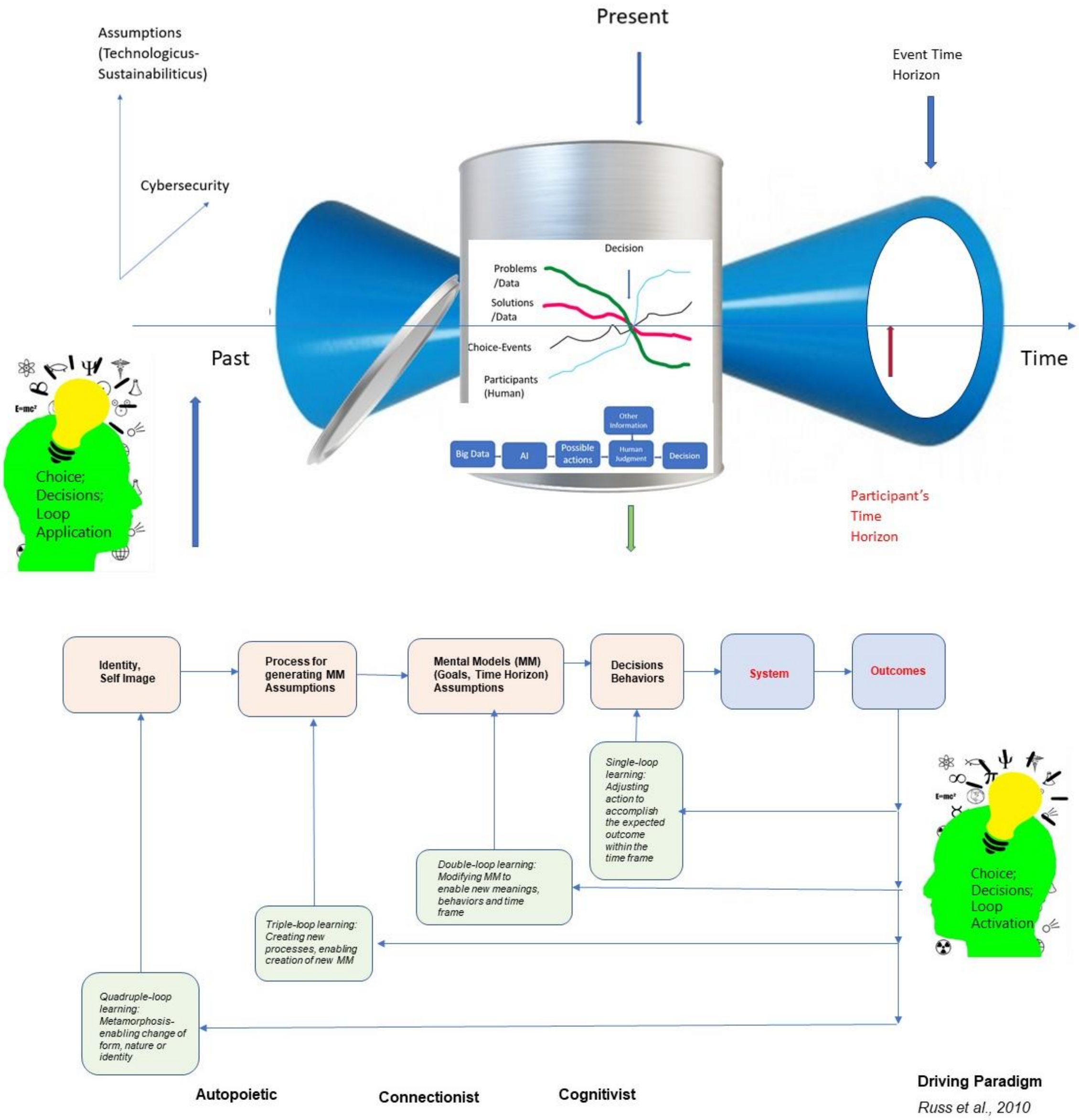

Figure 3. Individual model of quantum decision-making and learning (MQDM&L). Source: Ref. [1] Russ 2021, Figure 6b (p. 15) and Author's elaboration.

Such a collapse ("choice event" in terms used by the garbage can model of decision-making, Cohen et al. [34]) is critical in framing the issue at hand and the relevant solutions. Framing is known to be a major issue in making decisions; one of many cognitive and unconscious biases which could result in non-optimal decisions (see examples in [62,63]). The minimizing effects of such biases is another reason why incorporating ML and algorithms, both on the learning end and on the decision-making end, can improve the DM&L process. Moreover, incorporating ML and AI into the DM&L processes may be required since such technologies may force the actor to make a decision, or deal with a decision/learning directed by AI, that is NOT the choice they would have made, but is driven by the algorithm, which is forcing the timing of the choice event and the set of issues and solutions. As such, the model of DM&L used here must accommodate human-based DM, machine autonomous DM, and a mixed DM (see a simplistic model in Colson [64]).

Moreover, forgetting (or reframing) can also enable a completely new set of definitions of an issue and of alternative solutions. This might be required more frequently now than ever before (for example due to the shrinkage of half-life of knowledge [1]).

5. The Learning Feedback Loops—The Quadruple Loop Learning Model

Quadruple feedback loops are vital when a need (or opportunity) to frame, or reframe (an issue, solution, and/or an identity) arises because they provide the flexibility, if so chosen by the actor, to decide which feedback loop to use for the purpose of framing issues and solutions. In each case, when a different feedback loop is used, or due to a change in circumstance, the actor has the opportunity for new learning. Such learning may be framed within the present loop used by the decision maker or reframed if another loop is used. Using this model enables the decision maker and learner to make a conscious decision about the process they want to pursue (which specific feedback loop they want to engage), given the particular purpose they have in mind.

The first feedback loop is the traditional/standard feedback used for the purpose of adjusting actions to accomplish the expected/planned outcome within the planned time frame. Such feedback is not necessarily simple, as the discussion regarding "System Thinking" in the Fifth Discipline [65] illustrates, since the feedback can be positive or negative, with or without time lags, simple or complex (see also the Balanced Scorecard in [66]). Moreover, the first feedback loop can be used in multiple facets. It can be used as a traditional feedback control (looking backwards), as a concurrent control, or as a feedforward control [67].

Double loop learning was originally proposed by Argyris [68], who insinuated that the purpose of the feedback might require changes in goals, time horizons, and/or assumptions, achieved by developing new mental models and creating new meaning (e.g., [69]). The typical, simplistic example of such learning in the business context is the switch from market share to profitability as a goal (or visa-versa), since giving up on one, makes the other one easier to achieve.

Triple loop learning is defined as the creation of a new process, which could enable the creation of new mental models (see examples in [70–73]). Crossan et al. [67] proposed four processes to support such organizational learning: Intuiting, Interpreting, Integrating and Institutionalizing; at three levels: the individual, groups/teams, and the whole organization, enabling organizational strategic renewal. Kahneman et al. [40] recently suggested a number of organizational/institutional solutions to enhance this learning loop. For example, creating a role of 'decision observer' or creating a form that will result in 'aggregating multiple independent judgments'. They also proposed a number of procedural changes to schemas of how organizations should go about decision-making, such as by establishing a routine of 'sequencing information' or 'judgment guidelines; by creating 'shared scales grounded in an outside view'; or by 'mediating assessment protocols' [40] (pp. 222–223).

The quadruple loop learning proposed here is defined as enabling the all-embracing change of one's (actor and/or entity) identity; a metamorphosis (not renewal) of an organizational (or individual) identity; a complete change in form. For an organizational example, consider the case of the evolution of Starbucks from a small coffee chain in Seattle to the 'third place' [74] or the evolution of Google from a search engine into Alphabet, Inc. [75]. For an individual case, consider the case of a young entrepreneur that can morph into a serial entrepreneur [76] versus an entrepreneur who can grow a firm from a two-man garage into a global success (e.g., Steve Jobs; see [77]). The process described here is significantly different from the one (using the same name) described by Lee et al. [78] which identifies a different process between backstage and front stage for a public entity, but, is not encompassing the all-embracing change of the identity of the public organization.

The possibilities described here, and the range of choices (which one of the four choices/mindsets will be dominant?) enable an entity (an individual or an organization) to identify a variety of existing gaps and needs in order to acquire new knowledge or learn a new skill/capability. Here, the process described by Crossan et al. [67], the role of 'respect-experts' proposed by [40] (p. 226), or the models of learning as described in Russ [1] can be useful.

A good example of the complete model described above can be seen in the famous Apollo 13 movie, after the explosion of the oxygen tank. The plan for landing on the moon was cancelled, and the new mission (third loop learning) was to return the crew back home alive, which required a new mental model. Kranz's (Ed Harris) legendary response, "I don't care what anything was designed to do, I care about what it can do" is a wonderful example of changing one frame of the past (what it was designed to do) with a new look at the past (the design) but from a new mental model perspective (what it can do) and collapsing it with the new future, bringing the crew back home alive. This process dictated which module would be used for the trip back home, and on what trajectory, and enabled the astronauts to return home alive.

6. Ethics and Cybersecurity

Concerns regarding ethics and cybersecurity are included in Russ' [1] framework for KM that solidifies DM&L as one process. Obviously, such a discussion is relevant to the specific model of MQDM&L discussed in this paper.

With such a heavy emphasis on the importance of AI algorithms and big data, it is only natural that the models of ethical dilemmas/dimensions that include *Homo Technologicus* and *Homo Sustainabiliticus* be incorporated here. Their recently updated definitions are cited below

> "*Homo-Technologicus*—"a symbiotic creature in which biology and technology intimately interact", so that what results is "not simply 'homo sapiens plus technology', but rather homo sapiens transformed by 'technology' into 'a new evolutionary unit, undergoing a new kind of evolution in a new environment'" (Ref. [79] (p. 23)), driven by cost efficiencies and instrumental effectiveness within the techno-economic, universal and ontocentric perspectives and expecting adaptation of the 'homo sapiens' to the technology."

> "*Homo sustainabiliticus*—a symbiotic being in which biology, technology and morality intimately interact driven by optimization and the balance of costs of the technology solution, while modifying it to optimize the user's adaptation, especially regarding her abilities and the social acceptance recognizing cultural and symbolic differences and environmental responsibilities based on biocentric ethics and the socio-philosophical point of view within her cultural, social, physical, logistic and legal context and cognizant of the ethical dilemmas of adapting the technology to her needs, specifically at the design stage". [1] (p. 19)

The specific concerns (dimensions) listed in Russ [1] (p. 20) (2021, p. 20) regarding ethics, which are also relevant to this model are: (1) Are potential implications of the DM&L, considering the outcomes from the user/object perspective (the effectiveness aspect), taken into consideration? (2) Is the user/object provided with the "space" for "using/adopting the technology within their values and morals", in the autopoietic meaning of self-organizing, in "their context"? (3) Is the user sufficiently knowledgeable to make educated choices about the potential tradeoffs resulting from the specific outcomes and do they have the legal rights to do so? Figure 4 (below) delineates the space of the dilemmas as mentioned here. From a software development perspective, the evaluative framework proposed by Rieger and Majcherzak [80] points to how the ethical considerations described in *Homo Sustainabiliticus* might be weighted for inclusion in digital algorithms. On the other hand, Greene et al. [81] approach some of the same dilemmas from a modified *Homo Technologicus* perspective and have identified seven core ethical themes and two major areas of failure (which also can serve as opportunities for improvement). Regardless, ethical consideration must be a part of any DM&L model.

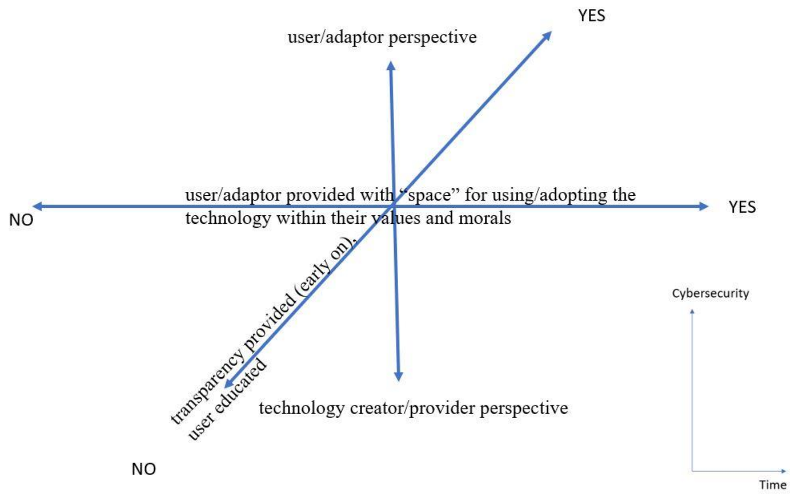

Figure 4. Three practical aspects of *Homo Technologicus* versus *Homo Sustainabiliticus*. Source: Ref. [1] Russ 2021, Figure 7, p. 20.

Another implication of the ample reliance of the MQDM&L on AI and big data is the need to consider cyber security as an integral aspect of the model. The framework for cyber security that was proposed in Russ [1], is suggested to be used in this model as well (see Figure 5 below).

Input from the *Homo Sustainabiliticus* paradigm

	Identify	Protect	Detect	Respond	Recover
Smart cybersecurity Systems & Services					
Incremental learning & dynamism					
Machine learning based security modeling					
Security data preparing					
Security data collecting					
Cyber infrastructure					

Figure 5. Cyber Security. Source: Ref. [1] Russ, 2021, Figure 8, p. 21.

7. Conclusions

The combined model of quantum decision-making, suggesting the collapse of the past and the future at the present time (when the decision is made), while explicitly defining the time horizon of the future under consideration and the quadruple feedback loop learning process could open new avenues both for AI/ML algorithms (improving on the efficiency of the process) as well as avenues to improve the effectiveness of organizational decision-making from the leadership/top management perspective. This new model also opens many new research avenues for academics both from the managerial perspective as well as from data and computer science perspectives. More specifically, two areas of future studies are recommended: (1) the amalgamation of decision-making with learning into a single process, framed by the collapsed time frames of future and past into the present, and (2) the use of ML and deep learning in framing issues, including the choice of relevant (to the issue) constrains. Both areas can be studied by using simulations in higher education and in training business executives to better prepare them for: collaborating with AI algorithms; dealing with unexpected situations; and making more effective choices in difficult situations, by having access to a broad set of choices, including the redefinitions of the identity in question. Additional areas of research could include new studies of lifelong machine learning [82], enabling a broader set of choices as a set for future study, and possibly connecting that with design thinking and experimenting at an accelerated pace, and prototyping to introduce new products/services into new markets.

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